Algorithmically Recognizing Gait Variance from a Sensor-Based System

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Dedication

This thesis work is dedicated to my Mom and Dad– who taught me I could be an astronaut, architect and mountain climber, all in the course of one afternoon. Thank you for sharing in my dreams, teaching me to try again, and for filling our home with a steady supply of books and graph paper. You love our family so selflessly, and have opened up a world of possibility for Rebecca and I. When I grow up, I don't care if I'm an astronaut, architect, mountain climber, or data engineer, as long as I'm just like you.

Abstract

Detection of Vascular Dementia in early stages of Cognitive Impairment is difficult to do in a clinical setting since the earliest changes are often discrete and physiological in nature. One major aspect of this is gait patterns. This project utilizes force-sensing platforms, motion capture, and EMG sensors to unobtrusively collect biometric data from an individual's walking gait patterns. Following data collection, a series of algorithms computes statistics off the gait cycles. In addition to previously validated biometric indicators of vascular dementia, including stride length, time in stride and swing phases of gait, time in dual leg vs single leg support, this system also examines metrics surrounding balance, lateral movement, and fine-grained gait analysis during critical transition periods of gait, when weight is transferred from one leg to the other. Secondly, by quantifying and analyzing machine learning algorithms, specifically deep learning time-series based models, onset patterns of vascular dementia are explored with an overarching goal of creating a system that will assist in understanding and diagnosing cases of vascular dementia. The proposed system provides a tool for which gait can be analyzed and compared over a long period of time and opens opportunity to increased personalization in health monitoring and disease diagnosis and provides an avenue to increase patient-centricity of medical care.

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1 Introduction

Elements of human biomechanics have long been used for disease diagnosis and prognoses. The proposed research seeks to detect gait features and build models of gait patterns associated with the onset of Vascular Dementia. By looking at key moments of the gait, such as when the individual is shifting their center of pressure from one leg to the other, differences in gait can be correlated with other measures of Vascular Dementia such as cognitive functioning.

This project has implications within the broader field of gait analysis, and detection of Vascular Dementia onset. Vascular Dementia onset is known to change to elements of gait, including the stride length, lateral movement during the stride, one-legged vs. two legged support, and worsening balance (measurable through center of gravity) during various key moments in the stride as well as increasingly present challenges in cognition [48].

Knowing these general trends about the development of Vascular Dementia, researchers have posed the question of whether such health changes could be used as an indicator for disease onset. Much of the research currently being done in Vascular Dementia is coming from the fields of human physiology and neurology [59, 60]. Such previous research has provided strong correlations between multiple forms of gait disturbances, including: (1) slowing pace, (2) decreased balance, (3) greater lateral distance between foot placements and (4) gait variability, more significant than in typical aging patterns, with cognitive decline and vascular dementia risk factors [60, 62, 51].

The major differentiation between previous work and the proposed project is that, in the case of the later, the innovation draws primarily from computer science rather than medical research. Building upon these findings, the project hopes to build predictive models based on features of gait, cognition data and biometric measurements.

Looking at changes during key moments of the gait cycle,it's expected that each participants gait will have low variability. Exceptions to this assumption will be described as a gait abnormality. In the case of a presenting gait abnormality, we anticipate that that the frequency, magnitude and duration of the presence of such features will fit a predictive model of the participants current and future cognitive health. Furthermore, we hypothesize that when simultaneously participating in cognitive tasks, the presence and magnitude of gait abnormalities will be correlated with more challenging cognitive tasks.

Classifying Phases of the Gait Cycle There are two phases of the human walking gait: stance and swing. In stance, the leg in question is planted on the ground, whereas in swing the leg in question is removed from the ground and swings to the forward position. The division of time between stance and swing is roughly 60 percent, 4o percent respectively. During the stance of one leg, is the swing of the other. However, its important to note that approximately 20-30 percent of the gait cycle is spent with both feet planted on the ground, (following the heel-strike of one leg but prior to toe-off of the other). This is known as the dual leg support and occurs at the beginning and end of a gait cycle as well as once in the middle. From pervious work, we know that we can identify three key moments stance phase in the gait cycle: (1) initial contact (heel strike), (2) mid-stance and (3) pre-swing (toe-off). Using center of gravity, and distribution of force, the intermediate phases: loading response, terminal stance, initial swing and mid-swing can also be identified. The fully constructed gait cycle is shown in figure 1. Using this knowledge, phases of the

gait will be identified from the force data, enabling us to look at the biomechanical features and any correlated cognition data collected during each of the investigated phases. Using the same theories, the transitions between single and dual support can also be investigated and the biomechanical differences of single and double leg support will be quantified.

Predictive Model Building Utilizing the above described dataset, we seek to apply various predictive modeling algorithms to the data in order to create an approximation of the normal gait for each individual participant. Concretely, we seek to answer how much data is necessary to create an accurate description of an individuals gait and how responsive these models are to detecting changes to the participants gait. To do this, a variety of predictive models from statistical descriptions of feature variance, fuzzy learning techniques, artificial intelligence-based algorithmic and machine learning models will be utilized. Through these methods we seek to build a model that can identify a the frequency and magnitude of a change to the individuals gait.

Currently, much of the statistical and machine learning applications of gait analysis in the medical realm looks at identifying critical events such as a fall freezing or other large gait-associated events [28]. Work has also been done on classifying of pathological gait abnormality in a short-term, clinical style assessment [1]. These studies include work on on augmenting force data collected from hardware into clinical measures of gait. From the shared themes of these findings and the proposed project, it follows that such ideas of individualized pattern recognition taken from computer security applications could be applied to the current findings of gait abnormality detection, to create a long-term model of gait in which to look for abnormalities. This focus on long-term gait modeling of the proposed project that differentiates it from previous work. This project seeks to add knowledge in the ways we build an maintain models of individual gait over a long period of time to accounting for the effect of

natural aging, while succeeding to identify chronic deterioration of gait.

The proposed research has the potential to impact our understanding of Vascular Dementia and the way we think about disease diagnosis. Early diagnosis of Vascular Dementia is challenging as the symptoms start our minor, followed by a gradual decline [44]. The proposed research explores ways enable earlier diagnosis. Additionally, the proposed research challenges the way we approach diagnosis tools. To enable earlier diagnoses, this research suggests that we look beyond clinical tests to behavioral patterns, which not only have the greatest impact on health, but often present indicators of chronic disease onset earlier than clinical tests could diagnosis the same disease [35].

2 Background

The use of technology as a tool in the medical setting is a growing area of research and development. With the desire to reduce healthcare costs and support patient-centered care, the integration of technology into medical processes is increasingly common [8]. At first these technologies were designed primarily for practitioners, managers and other professionals in a healthcare setting. However, as telecommunication and mobile computing technologies improved, systems that interact directly with with patients outside of the healthcare setting, became more prevalent [9].

Perhaps the strongest force driving this innovation is the growing interest in evidence-based and personalized medicine. The origins of evidence-based medicine can be traced back to to mid-nineteenth century Paris where physicians "conscientiously and explicitly" [50] used outcomes from their previous cases to make current care decisions. The rise of technology has greatly changed how evidence-based medicine is practiced, but the core idea has remained the same – incorporating clinical evidence from systematic research into health decisions, particularly diagnosis [50]. Likewise, personalized medicine looks to base health decisions on individual health records, the idea being that individuals' patterns and health history should be incorporated into health decisions. Often referred to as N-of-1 studies, mobile technology has proven to be of great utility in the execution of these studies to collect, record and communicate current data with providers [38].

Personalized medicine tools have been applied to many realms of health, including preventive care, chronic disease management and monitoring of patients. Such

systems allow us to ask previously unanswerable questions to better understand the connection between behavioral choices and health. There are many benefits to such a system, however they come with many challenges. Because of the sheer mass of data, there is necessity to develop analytical methods to process raw data into actionable knowledge for patients and their providers [45]. In addition, regulatory, financial reimbursement and technical security hurdles remain in need of consideration.

This research looks at the potential of data from a mobile sensor system and machine learning tools to diagnosis vascular dementia earlier in onset. Medical research has begun to recognize patterns in vascular dementia onset, however, this is difficult to identify and study as clinical tools can't diagnosis the disease until much later in the disease progression. The research seeks to combine what is known about sensor systems, machine learning, vascular dementia and early indicators of disease to develop a system that can predict vascular dementia onset.

2.1 Progression of Vascular Dementia

Progression of Vascular Dementia generally represents a stepwise decline appearing suddenly after episode and aggravated from following episodes, but without the continuous decline common to Alzheimers Disease. Vascular Dementia transitions from preclinical to Vascular Cognitive Impairment to Vascular Dementia, of which can be sub-classified as mild, moderate or severe. To understand diagnosis, the symptoms and expected progression at each of these stages must be considered.

2.1.1 Preclinical Stage

The initial stage is often described as silent as the brain begins to change without measureable symptoms being displayed; changes are not detectable on tests and

symptoms patient experiences are not diagnosable. Because of this, much that is known about the preclinical stage of Vascular Dementia is based on retrospective evaluations of records of diagnosed cases. One such study found that patients had memory complaints 12 years prior to diagnosis and had experienced declines in activities of daily living 5 to 7 years previous to diagnosis [61]. While Vascular Dementia patients had memory complaints 12 years prior to diagnosis, cognitively, there is comparatively less deterioration in the preclinical stage as compared to other forms of Dementia. Patients with incident vascular dementia deteriorate earlier and faster in daily functioning, especially the more physical activities of daily living such as activities, arising, dressing and grooming, eating, hygiene, grip, reach, and walking, as compared to other forms of Dementia that experience the first changes in cognitive activities such as finance management, phoning, medication use, housekeeping, and meal preparation [53], [61]. In addition, the preclinical stage is often accompanied by symptoms of depression, particularly motivation-related such as lack of interest, loss of energy and concentration difficulties. This association still remained significant after adjusting for memory complaints, showing that depressive symptoms are not merely a by-product of perceived cognitive difficulties [4].

2.1.2 Vascular Cognitive Impairment

The progression from preclinical to Vascular Cognitive Impairment is a very slight transition. The Vascular Cognitive Impairment stage is loosely defined as cases where one or more cognitive domains becomes significantly affected [12], [55]. At this stage in the disease, symptoms are becoming clinically detectable and while noticeable in daily living, not generally too limiting in this respect.

2.1.3 Vascular Dementia

Onset of Vascular Dementia is marked by cognitive impairment severe enough to interfere with everyday activities. The onset of Vascular Dementia can be divided into sub-domains of mild, moderate, moderately severe and severe.

2.1.4 Mixed Dementia

Another factor to consider is the onset of other forms of cognitive impairment in addition to vascular dementia, referred to as Mixed Dementia. Mixed Dementia refers to cases of Vascular Dementia where symptoms of other cognitive impairment, not originating from the vascular episode, begin to affect the patient in addition to the symptoms of Vascular Dementia already present. Approximately 15 percent of cases of Vascular Dementia present with other forms of cognitive impairment[47]. Identifying the onset of other cognitive impairment and the relationship between the Vascular episode and these other cognitive impairments is one of the great challenges facing research in this area.

2.2 Early Indicators of Dementia

Predicting Vascular Cognitive Impairment before the disease progresses further is a significant challenge. Vascular dementia in particular is of interest because patients often experience "step-wise" deterioration as opposed to gradual and symptomatic improvement following acute events. In addition, in the subcategory of vascular dementia, mild cognitive impairment seems equally if not more prevalent than full onset of dementia symptoms [29]. Researcher have identified several indicators of vascular cognitive impairment including impaired social or occupational functioning, motor

activities, visual processing and abstract reasoning [29]. However, one challenge is to transform these rather abstract indicators into quantifiable and actionable metrics.

One developing area is that of gait analysis. This could be stride length, lateral balance or effort exerted (measured using heart-rate monitor for example) for a particular class of activity [16]. Motor activity metrics focus on measuring ease, frequency and type of movement. Gait has clear links to motor activities, but it also has an interesting link to visual processing since the visual system in largely correlated with balance. In comparison to other physiological feedback systems, Visual information is typically more sensitive and is believed to play a significant role in fine-grain adjustments to balance, especially in the feet and ankles. [34]. In patients with Vascular Dementia onset, impaired visual processing could be recognized in balance and gait discrepancies. Various gait metrics have been investigated and their potential to identify vascular cognitive impairment has been evaluated.

2.2.1 Distance and Speed Metrics

In respect to gait analysis, distance and speed are typically measured in terms of a single stride. To understand what these metrics quantify, it's important to understand the components of a stride. Stride length is measured as the distance between two consecutive footfalls of the same foot. In addition, a single stride can be broken down into components, commonly, swing time and stance time. Swing time refers the time when only one foot is on the ground. The stance time refers to the time when that foot is on the ground. Distance and speed metrics are often in reference to either a complete stride or a component of a stride. [60]. Shorter stride length has been linked to a increased chance of mild cognitive impairment [16]. Similarly, the a slower gait can indicate motor function concerns, thus measuring the velocity or cadence (steps

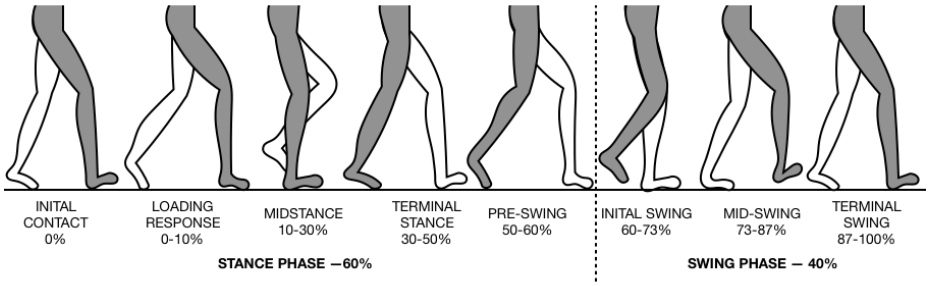

Figure 2.1: Normal Gait Cycle (by percentage of time in each phase)

per minute) can also provide useful information [60].

2.2.2 Gait Disturbances and Difficulties

On a similar vein, measuring gait disturbances or difficulties takes stride metrics and looks for abnormalities or inconsistencies between multiple instances over a time period. In these methods, a range of acceptable metrics is defined and measurements outside that range are considered a disturbance [59]. This idea comes up frequently in fall detection, but the idea of creating a customized range based on user data rather than setting a predefined range, is one application of this idea that may prove useful to this research.

2.2.3 Velocity, Rhythm and Variability of Gait

Velocity, rhythm and variability of gait also look at comparing multiple strides in a time frame against each other, however, rather than looking for outliers, these metrics attempt to recognize patterns in the data and cases where these patterns are not true [59]. One example of this is measuring the percentage of the stride that is spent on the swing verses the percent on the stance. Typically, the swing takes 40 percent of the stride with stance taking the remaining 60 percent of the time. [18]

Velocity, rhythm and variability measures are aimed to quantify how much a gait changes in this respect over a time period.

2.2.4 Stability

Stability and width of base, while associated with velocity, are largely metrics of balance. Stability looks at the consistency of weight patterns on a foot. Inconsistent (variable) patterns of weight distribution could indicate the individual is "shaky" and struggling to balance. Width of base is another way we can measure stability. Width of base refers to how far apart a individual's stance is. A wide stance can indicate balance concerns as well [18]. Finally, double support, when both feet are in contact with the ground at the same time, can be measured while an individual is walking. Longer double support time was seen in participants with more balance concerns. [60].

2.2.5 Outstanding Challenges in Gait Analysis

A challenge facing this realm of research is that aging causes many of these occurrences. Therefore successful research in this field has looked not only for the presence of these indicators, most of which are likely common in an aging population, but also at the extent to which an indicator is present. This aims to separate changes typical of aging from those of dementia onset, however, this continues to be a challenge in this field of study [16, 29]. In addition, since the indicators at this stage are largely behavioral and physiological it is very challenging to identify these in a clinical setting. In addition, the way these indicators present in each patient differs and in many cases, a patient may experience only a subset of all the indicators mentioned. Adjusting for individual differences and variation during analysis is another challenge of this field.

2.3 Sensors

The sensor system being used to quantify the patient's patterns plays a crucial role in understanding the early identifiers of Vascular Dementia onset. There are many different approaches to sensor networks. Infrastructure area networks are comprised of sensors incorporated into the surrounding environment such as cameras, sensors on doors, pressure mats or bed occupancy sensors. Body area networks are sensor networks that are attached to the patient to monitor brain activity, heart activity, glucose and muscle activity commonly used for personalizing medical treatments. [32, 42]. Within the realm of on-body sensors there are several sub-domains:

1. Bioelectric Sensors: measures energy generated when nerve or muscle cell is stimulated beyond a threshold level (e.g. hear activity).

2. Biomagnetic Sensors: captures magnetic fields of specific organ or tissue created by action potential (e.g. peripheral nerve activity).

3. Biochemical Sensors: changes in chemical ion concentration (e.g. Glucose-level sensors, blood oxygen concentration).

4. Biomechanic Sensors: Mechanical functions such as motion, displacement, tension, force, pressure or flow (e.g. inertial sensors, blood pressure sensors, goniometers).

5. Bioaccoustic Sensors: Noise caused by vibrations of biological events using transducers at skin surface (e.g. heartbeat monitor, blood flow monitor).

There are many trade offs between on-body sensors and infrastructure sensors. For one, on-body sensors are more intrusive in patient's daily activities. However, in the realm of healthcare, such data is often the most telling. This becomes a balancing act

of creating a system that is both accessible for patients while also providing detailed, actionable data for decision making. For the remainder of this section, we look at ways to quantify the indicators of vascular dementia previously discussed using sensors as well as how to assess the performance of such a system.

2.3.1 Technology to Analyze Gait

As previously discussed, there are many different metrics we can use to describe gait, including distance walked, speed, disturbances or difficulties, velocity, rhythm, variability, stability and width of base. Depending on the chosen system, other metrics, such as angle of joints, ground reaction forces, routes taken or terrain types covered could also be aggrigated from the data collection process [43]. Most research conducted on gait analysis in the clinical setting relies on health care providers observing and manually identifying the presence or prevalence of certain features, though three prevalence forms of sensor-system have been utilized in gait analysis: motion capture monitoring, floor-based sensors, and on body sensors [43]. A growing form of on-body sensors, mobile devices and mobile-connected sensors, such as pressure sensing insoles, have been proposed for gait recognition and analysis tasks [24]. Such technologies have shown the capability to streamline this into a single process.

Image processing and camera based tracking systems usually revolve around the use of several specifically placed cameras in a space. These can utilize threshold filtering, background segmentation or a reflective markers to distinguish key features features of the image for later analysis. Depth measurement, frequently accomplished using camera triangulation, these methods obtain for the user a representation of the image from in relation to a viewpoint [43]. Such systems provide a way to not only measure metrics of gait, but also look at the joint angles; a distinguishing feature of

image processing and camera-based tracking systems.

Floor based sensors, can also be used to measure gait. Typically such systems will preform computations of force and moments, which can be aggregated into center of pressure, and used to compute the gait phases. Ground reaction forces is on data component that is unique to this type of system. The most complex of such a system can compute the distribution of pressure underneath the foot [43]. Recent developments combine pressure sensing with the smaller scale of a on-body sensor.

Pressure-based insoles have been developed by numerous groups as a way to monitor gait. These sensors are typically designed as an insole to be worn inside a shoe and have multiple pressure sensors throughout the insole that can identify how much weight is being exerted in a location at a particular time. From this, center of mass and the velocity of the gait can be be derived. In addition, these systems excel at identifying stability, balance and the base stance [30]. For example, such a system could determine which part of the foot bears most of the weight of the individual when flat footed or if when they are motionless, there is a continuous shift to where their center of mass is, indicating issues maintaining a balanced stance.

Wearable sensors such as pressure-based insoles encompass a wide variety of sensors that can be place on the body, commonly the feet, knees and hips to measure specific characteristics of gait. One example of this is the use of an EMG sensor on specific muscles of the leg. This also encompasses the use of accelerometers, gyroscopes, inclinometers among many others [43]. With the rise of mobile devices containing more than a few of the mentioned sensors, the potential for monitoring gait through a mobile device is a strong possibility.

Mobile device sensors are also taking a center stage in gait analysis. Mobile devices include a multitude of sensors, including a accelerometer, digital compass, gyroscope, proximity sensor, ambient light sensor, GPS, microphone and camera [33]. Using these

sensors, a device can be configured to track elements of gait such as stride length, base width, velocity and variability as well as distance travelled and speed travelled [25]. In addition, applications can use activity recognition algorithms on the device to log data only when the desired activity is present, which improves the specificity of the data being collected. A broader look at gait detection on mobile devices shows that such technology is already shown successful in distinguish an individual from others [10]. Mobile devices benefit from increased variability of sensors and computing power that makes them capable of more powerful aggregations, measuring speed, distance and classifying motion in real time where independently acting sensors must upload data to a separate application for computation.

2.3.2 Tracking Vitals over Time

In addition to monitoring gait, vitals may also prove meaningful to collect. In previous work, vitals such as heart rate or blood pressure are shown useful for analyzing how much exertion is required to preform a certain activity [24]. For this purpose, Sensogram Technologies' SensoSCAN Vital Monitor has been selected to collect a continuous stream of vital data throughout the duration of the activity. The SensoSCAN reads blood pressure, heart rate, oxygen saturation and respiration rate at a rate of approximately every 4 seconds. From this data an activity level is approximated (on a scale from 0-5) which is based on the data stream and amount of movement detected by the device.

2.3.3 System Performance

From a patient's prospective, ease of use, comfort and durability are important factors in a application. A device that has a clear interface, is easy to calibrate and

works without patient intervention are all components of "ease of use". In addition, patients are looking for a device that, if on body, does not effect their lifestyle [32]. The accuracy, precision, sensitivity, selectivity, stability and highly dynamic range of data produced by the system are all important aspects to consider during system design that effect how the system performs [32, 36]. Understanding potential strengths and weaknesses is key to foreseeing any possible concerns within the data produced. In addition to the information quality, there are multiple technical challenges to take into consideration to sensor system design including networking, power consumption and security [32]. For example, if a system is meant to be used continuously, the battery life on the device and any external sensors will have to be high enough to last throughout the day and must be able to fully recharge in 8 hours. In addition, there is the question of how often to transfer data of of the sensors and devices, especially in the case of continuous monitoring.

2.4 Machine Learning

The problem of diagnosing vascular dementia early in onset is a challenging one. For one, not all symptom patterns or indicators will be present in an individual patient, but rather a subset of these. The ideal system would have to flexible enough to account for the variability in disease onset, while also not being so flexible as to create a multitude of false-positive results. Another challenge is that behavioral and physiological patterns differ between individuals. To account for this, the system must learn to conform the individuality of measures to the known pattern, to create personalized and actionable knowledge. To accomplish this, there are three learning model sub-disciplines we explore: two part classification models, random forests and neural networks.

2.4.1 Two-Part Classification Models

Two-Part Classification Models use input information to classify data into one of two categories. This model has been largely utilized in diagnosis applications since the goal of determining the presence or absence of disease fits well with the structure of the model. One area that has used long been using the idea of Two-Part Classification Models is Breast Cancer diagnosis. In these projects concerns often related to noise in the data and the sheer volume of information being given as input [39]. Two-Part Classification Models have also been used in the realm of cognitive health diagnosis. The struggle of noise and data volume remain a relevant concern in these cases, but with the added challenge of differences of disease presentation among the population. In breast cancer diagnosis, certain metrics are strong indicators of disease such as the results from analyzing a mammogram. However, in cognitive diseases, it's proven more challenging to find a metric or composite of metrics that can separate positive and negative cases since the onset characteristics vary from person to person.[31].

Evaluation of Two-Part Classification Models

In two-part classification, evaluation is largely based on the predicted value compared to the actual classification. As is shown in the figure 2.2, comparing the predicted outcome, positive (p) or negative (n), with the actual value, positive (p) or negative (n), gives us the count of True Positives, False Negatives, False Positives and True Negatives. From this we can aggregate the True Positive Rate (recall), False Positive Rate, False Negative Rate and True Negative Rates as shown in figure 2.2.

		Prediction Outcome		
		p	**n**	**total**
Actual Value	**p′**	True Positive (TP)	False Negative (FN)	P′
	n′	False Positive (FP)	True Negative (TN)	N′
	total	P	N	

Figure 2.2: Confusion Matrix: Actual vs. Predicted

2.4.2 Random Decision Forests

Random decision forests expand on the capabilities of decision trees while also aiming to improve the accuracy of the model on unseen data. Decision Trees, while intuitively appealing and fast, are at high risk of overly adapting to training data. To overcome this, the idea Random Forests – using many Decision Trees, all based on the same data but branching differently, came into existence. In a random forest, each individual decision tree will make a decision. Following this, all the decisions will be collectively considered, and the most common decision becomes the final output of the forest. Some random forests will use weighting mechanisms to express how accurate a particular tree is (and how much it should or shouldn't be listened to when deciding on the final output) [19].

While less-frequently seen in gait analysis, Random Decision Forests have shown great success in taking forming a classification of the severity of Alzheimer's Dementia onset MRI, biomarker measures and categorical genetic information. This study in particular highlights the potential of combing different types of data into a model, as well as the accurately ability to model and predict in a complex system. [14].

2.4.3 Support Vector Machines

A support Vector Machine is a supervised learning method that, given a set of training samples belonging to predetermined categories, separates examples as points in dimensional space (based on the number of features) where the examples are divided by a clear gap that is as wide as possible. Alternatively, an unsupervised approach attempts to find natural clustering of the data into groups. In both cases, new data is maps into the group it most closely resembles [56].

Support Vector Machines have also been used as a classification model for gait. One particular study looked at distinguishing between two classifications (young and old participant groups) based on gait. In this study, the distribution of minimum foot clearance is calculated fro each participant. The minimum foot clearance is measured from a side-view of the participant. From the resulting distribution, multiple features are identified and used to feed into the Support Vector Machine, such as the standard distribution of the distribution, or the inter-quartile range. With 3-5 features, the model can reach above 90 percent accuracy in assigning the correct classification [3].

2.4.4 Improving Outcomes

In addition, bagging and boosting techniques can be used in forests or ensembles of models to improve the overall accuracy. Bagging does so by creating multiple sub-sets of the original dataset to pass into different models. This can improve accuracy as models built on different data sets will naturally isolate or focus on different features. Used in an ensemble or forest, this can improve the overall understanding of the data and thus the accuracy. Boosting is another way to improve the accuracy of models simply by manipulating what data is passed into the model. In boosting, all data starts with an equal probability of being chosen for a sub-set on which the

model will be trained. Data that is correctly classified will become less likely to be chosen, where data that was incorrectly classified will become more likely to be chosen in subsequent training rounds. In doing so, the model is exposed to more difficult classes more often (thus increasing the amount these classes are seen by the model), and easier-to-classify classes less often. The goal of boosting is to improve the models performance on classes where the greatest loss of performance is happening.

2.4.5 Deep Learning

Deep learning, rather than trying to learn the mechanics of a specific problem, simply seeks to find a meaningful data representation to clarify the problem. In such a system, variable weighting is applied to a series of inputs, propagated through further weighted hidden layer nodes, to arrive at a conclusive output node. A neural network is trained through a learning process that provides feedback to nodes, iteratively refining the weighting at each of the respective layers. In a supervised-learning network, examples of inputs and corresponding desired outputs are simultaneously presented to the network. The network evaluates correctness of estimates against the actual values and adjusts the nodes at each level (back-propagating from the output node downward through the layers towards the input notes) with the goal of accurately representing as many examples as possible [7].

Borrowing from the findings in the field of computer security, gait patterns are recognizable by neural networks, as well as being specific to a particular person. In security, this has proven to effectively identify and authenticate a user based on their gait [63]. In terms of healthcare, this has two implications. First, that neural networks can be used in a time-series based gait problem and secondly, that gait is unique and distinguishable on an individual level.

In terms of gait analysis, the use of neural networks provides a methodology to extract and observe information with the goal of finding patterns within gait data, as opposed to statistical evaluations. Through the process of weighing, information is extracted and observed in different ways with the goal of finding universal truths and trends within the different representations.

Time-series based deep learning models appears to most accurately fit into our proposal. Because of the complexity of time-series data, we will consider the use of a network that can reduce the size or complexity of data we are working with, without loss of meaning.

2.4.6 Developments in Gait Analysis using Neural Networks

Neural Networks have been proposed for some gait classification and analysis problems. The idea was first proposed in 1993 as a classification decision making tool for distinguishing between pathologically effected gaits from healthy control gait. The study collected multiple samples of data collected at the time of heel strike. This study presented a tool that can diagnosis pathological from healthy gait patterns without having any built-in model or understanding of gait. In this example, the network output not only classifies the input pattern into the pathological or healthy grouping, but also describes how well the particular input fits into the pattern of the assigned class. For example, and ouptut of 0.9 would indicate a more pathological gait than an output of 0.6, which suggests a more subtle classification [23]. Additionally, it was noted that an evaluation of the weights within the network provides insight into the variables contribute to what degree to the output variable, though the model still proved to be controversial, and was thus verified against a current statistical classification model [23].

Following Holzreiter and Kolile's intial findings, Barton and Lees extended the challenge of gait classification to a three-output classification problem using hip and knee joint angles – measured using reflective markers on the participants in a motion capture system [2, 15, 41, 40, 13]

Research as also explored the use of neural networks to explore the relationship between metrics such as EMG and kinetic features. [52, 17]

Up until this point, neural networks were standard multilayer feed-forward models. However, since these initial investigations, the model types and purposes of neural networks in gait analysis has diversified Inputs have become more complex – feeding full temporal waveforms into the network (rather than aggregating out small portions of the the data for analysis by the model, speaking to the importance of the gait being evaluated as a whole [7, 10].

2.4.7 Recurrent Neural Networks

Recurrent neural networks come into the picture when we consider learning in a temporal, connected sequences. In a recurrent neural network, each subsequent step builds upon the the output of the previous moment. This treating past outputs as input to the next time step is done through input units referred to as "context units". Thus the decision a recurrent neural network makes at time T-1 will affect the decision make in time T, as it will be passed back into the network as context for the next decision. This loop integrating past decisions to future ones distinguishes a recurrent neural network from a traditional forward feeding neural network.

This added complexity lead to a more complex backpropagation equation in Recurrent neural networks, referred to as backpropagating through time. In this, backpropagation flows through the context units, into the previous state (T-1) of the

neural network, which would then link to the previous time-stamp (T-2) and so on up the chain until the weights have been adjusted through all previous instances of the neural network.

A major drawback to Recurrent Neural Networks (and many layer forward feeding neural networks) is the problem of vanishing gradients. This refers to cases where the weighting of the nodes across the board become too small for the network to use for learning [22]. The backpropagation in recurrent neural network relies on gradient-based learning methods. Each weight in the model is updated with respect to the error function and current weighting for each iteration of training. However, sometimes, gradient will diminish to the point that the weight will not change in value from time to time, effectively preventing the neural network from future learning [22, 20].

The Long Short-Term Memory Network was designed to address the problem of vanishing gradients by encompassing more context information within the network (called a memory unit) [20]. In addition to addressing the problem of vanishing gradients, the Long Short-Term Memory Network design excels in problems with long time lags between connected data points (many steps apart), making it a fitting complex temporal data [21].

2.4.8 Waveform Signal Processing

Because of the noisiness of the kinematic signals, various signal processing to prepare data has been proposed. Key objectives of signal processing include maintaining the shape of data or smoothing spiking data. Studies have shown that filtered data may produce more accurate results in comparison to models built with none filtered, perhaps due to a reduce in complexity from noise [7]. When building models off kinematic data, especially for the prediction of kinematic data, signal processing may be

an important step.

2.4.9 Expert Acceptability of Machine Learning

The medical field is slowly becoming exposed to more and more applications of machine learning. This is especially true in the realm of diagnosis. Authors Pazzani, Mani and Shankle, who's research focuses on identification of dementia earlier in onset using Knowledge Discovery in Databases wrote a paper on designing algorithms in a way that improves their acceptance by the medical community. One point they mentioned was that medical professionals look for consistency in both method and outcome with current knowledge [46]. Therefore systems that start with the current knowledge base of the medical community and make alterations to that knowledge are more likely to be accepted than a newly learned model (even if it's based on the same data!) For example, suggesting changing a classification to reduce false positives has a better change of being accepted than a entirely new classification model, even if it appears more effective. Transparency of model design is also an important factor in a healthcare-oriented machine learning algorithm. In the case of decision trees or classification systems, physicians able to trace to some degree how input data gets transformed into the output results. However, since neural networks lack this transparency, physicians tend rightly to be more hesitant and will look to see consistency between the output and the current understanding of the particular area [31].

2.5 Fuzzy Futures

In addition to machine learning techniques that compare various samples, research has also explored the possibility of using genetic algorithms and fuzzing methods to

create a population of "possible futures" given the one current sample. Each item in the population is derived from the same original sample but with some variation. This idea can be combined with a temperature that determines how differentiated the population item is from the original sample.

Much research has been done in respect to Fuzzing data, particularly in time-series prediction problems. George G. Szpiro was one of the first researchers to discuss the idea of approaching chaotic data series with chaotic analysis strategies. This work gives some insight into processing and understanding noise and signal processing in densely populated time-series data [57].

2.6 Previous Work

Dr. Joe Verghese from the Einstein Aging Study has been looking how gait dysfunction and cognitive impairment co-relate in various forms of dementia. A paper published by he and his team in 2007 document their research looking at how rhythm and variability of velocity patterns co-present with dementia [60].

The Einstein Aging Study is a longitudinal study aimed to identify risk factors of dementia. Individuals with dementia at the beginning of the study were excluded. Participants return at yearly intervals for basic evaluations. This particular study is a cohort of the Einstein Aging Study that is comprised of 427 participants. Beyond the cognitive assessment that is typical for participants in the Einstein Aging Study, this cohort participated in gait during the yearly assessment. The study was conducted for 5 years, but because of individual circumstances, the average time of participation was 2 years per participant.

This study used a pressure-sensor walkway 180 inches long. Participants traversed the walkway two trials per visit. The following parameters were collected:

- velocity (cm/s)
- Stride Length (cm)
- Cadence (steps per minute)
- Double Support ("Time elapsed between the first contact of current football and the last contact of previous footfall, added to the time elapsed between the last contact of current footfall and the first contact of next footfall."[60].)
- Swing and Stance Time (as defined above)

From this data, the measures of velocity, rhythm and variability were calculated. Among these factors, only velocity was associated with a decline in any cognitive domain. Over the five years of follow up, 33 participants developed dementia. Variability and Rhythm measures were predictors of future dementia and the velocity factor in particular was able to predict risk of Vascular Dementia.

In addition, this paper introduced an important conversation about the potential damage of false-positives, especially in the prediction of dementia. Since dementia is treatable but incurable, the prospect of being diagnosed causes fear for many patients. Technology systems and experiment design should therefore be as unobtrusive as possible and designed in a way that prioritize the patient's well being before all else.

This paper outlined two limitations of this research: gait variables were selected based on prior studies and different levels of activity or stresses were not introduced. We seek to advance the knowledge of this research by addressing these two concerns and incorporating machine learning techniques into the process of evaluating possible indicators.

3 Methods and Implementation

In this user-study, we will be evaluating our ability to computationally track gait patterns, over a 7.5 minute duration. The duration was chosen with the goal of reaching a point of fatigue in participants [37]. A primarily outcome will be identifying artifacts of gait and inter-sample variability. A secondary outcome will be to analyzing intra-sample variability among multiple samples from the same research participant. We will discuss the procedure for collecting data samples, pre-processing collected data and exploring relationships in this data.

3.1 Study Description

Gait data will be collected via a force treadmill. Each data collection session will consist of a trial consisting of a 7.5-minute walk at 0.5 miles per hour. Protocols for the Kinematic data collection are outlined below.

Kinematic Data Collection

Kinematic data will be collected in the Computational and Applied Human Neuromechanics (CAHN) Lab. This lab is outfitted with a dual belt force treadmill for collecting forces under the feet during walking. The treadmill has handrails on both sides and in front. Prior to data collection, the participant will receive an orientation of the system, including how to safely get on and off the treadmill and agree upon a communication protocol. The treadmill is equipped with an emergency stop button.

To reiterate, we will be observing the gait of participants in a closed environment; there are not interactions or interventions being tested as a part of this protocol.

During data collection, the treadmill belts will be set to move at 0.5 miles/hour for 5 minutes. This has been identified as a slow enough pace for an older population that may use the system in the future [6]. A Confirmation and Countdown protocol will be discussed and agreed upon by researcher and participants prior to data collection. When starting and stopping the belts, participants will be asked if they are ready for the belt to start/stop. No action will be taken until they respond. Once they have acknowledged, the countdown (Starting in Three, Two, One or Stopping in Three, Two, One) will be given by the researcher before stopping/starting the treadmill. The researcher will remain by the controls throughout the duration of the data collection. Any sign of participant distress, verbal or otherwise, the researcher will stop the belt using the same confirmation and countdown procedure outlined above.

3.1.1 Study Duration

The study will take approximately 10 to 15 minutes for the inclusion questionnaire and .5 to 1 hour for data collection.

The duration anticipated to enroll all study participants is expected to take two months. The duration anticipated to complete all study procedures and data analysis is one to two years.

3.1.2 Research Participant Recruitment and Voluntary Participation

Participants have be recruited through email from the student, staff and faculty population at the University of Minnesota Duluth. Participation is voluntary, and

not linked to any other facility participants hold.

Inclusion Criteria is as follows:

- participants must be older than 18
- there must be no known cardiovascular neurological or muscular problems as identified by the inclusion questionnaire.
- There must be no known mobility difficulties, any problems with balance or dizziness, any serious musculoskeletal injury to legs, feet or back, any chest pain or shortness of breath with exertion, hypertension or any history of heart attack as identified by the inclusion questionnaire. Answering yes to any of the above conditions will eliminate the individual from further participation.
- If a participant is over the age of 40, the participants description of weekly exercise must include some form of moderately strenuous exercise taking place on land more than 3 times a week to be included in the study.

Exclusion Criteria is as follows:

- No children will be included.
- No individual over the age of 70 will be included.
- No individuals with muscular or skeletal related health issues will be included.
- No vulnerable populations will be included.

Participants will be recruited from the University of Minnesota, Duluth (UMD) community. Subjects will be recruited using email. Email will outline inclusion and exclusion criteria and invite participation. Subjects will self-identify by responding

to emails. Please see attached for an example email. No subjects will be recruited from medical records. To determine eligibility for the study, participants will complete an initial inclusion questionnaire to determine whether or not they are eligible.

Risk and Benefits to Participants

The risks of this study are minimal; similar to the risks associated with walking down the street.

Participants will get 7.5 minutes of exercise, and will be offered access to their raw data files upon completing the study.

Informed Procedures and Consent

Researchers will explain and demonstrate all procedures including: (1) getting on and off the treadmill, (2) preparing for the treadmill to stop and (3) indicating distress. In addition, researcher will talk about data usage and data management plan. Researcher and participant will discuss any concerns or more information needed. The researcher will confirm that inclusion and exclusion criteria arr properly met. Following, this, participant will choose whether to consent to the study.

Withdrawing from Participation

If a participant withdraws from the study prior to or during data collection, their data will be removed from the study. If data has already been unidentified, the data will continue to be analyzed, but no further data will be collected.

3.1.3 Data Management and Confidentiality

Upon completion of the inclusion criteria, qualified participants will be assigned a random number that they're data would be associated with. One look-up will exist, but will only be used during the data collection phase. During analysis, data will be void of any identifying information. Participants will not bet contacted with results from analysis.

3.2 Data Collection Process

Our implementation revolves starts with unification of data files, data preparation and processing, and computing aggregate data measures. Once collected, data is exported into separate .CSV files for each of the force plates, EMG sensors and Motion Capture system. Our system first combines these four files into one file. In addition, preprocessing takes place including reformatting values into the correct numerical format and removing leading and trailing zeros in the data file. Finally, naming conventions are established in this stage. Following the creation of the unified data file, aggregate measures including center of pressure, end of unloading and toe-off events, and gait phases (single vs. double leg support) are calculated off the data set. These aggregate values are added as additional columns in the dataset. This process is overviewed in the flow-chart in 3.1. Each of these tasks is outlined in the paragraphs following.

3.3 Data Aggregate Values

Three pieces of data are aggregated and incorporated into the existing data set: center of pressure, gait phase and end of unloading/toe-off events.

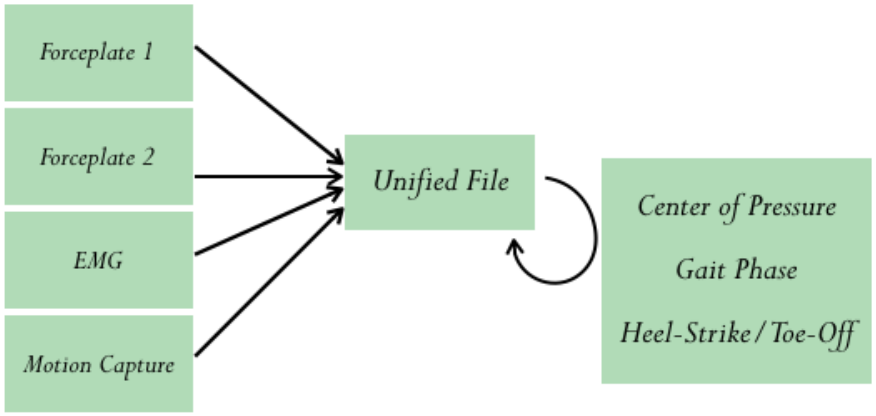

Figure 3.1: Gait Data Collection and Analysis Process

Figure 3.2: Bertec Treadmill

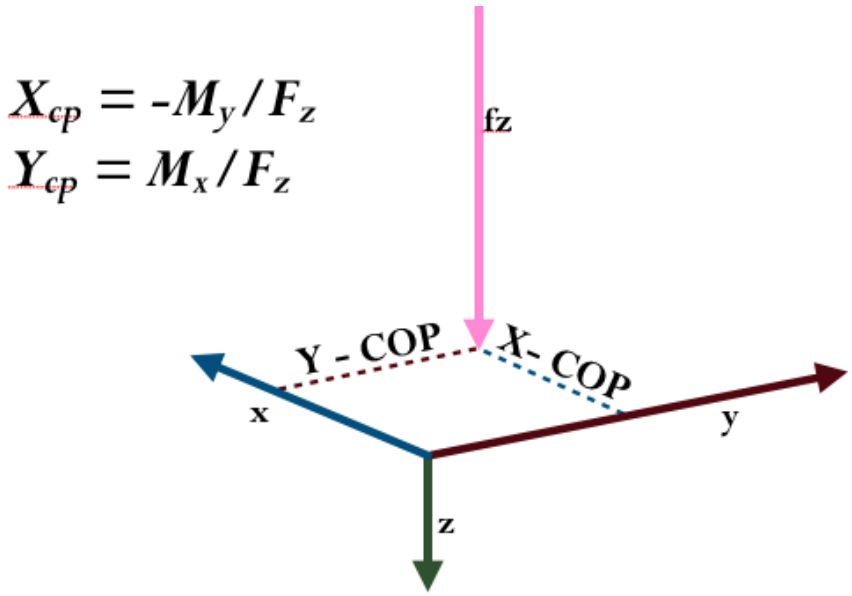

Figure 3.3: Center of Pressure Calculation

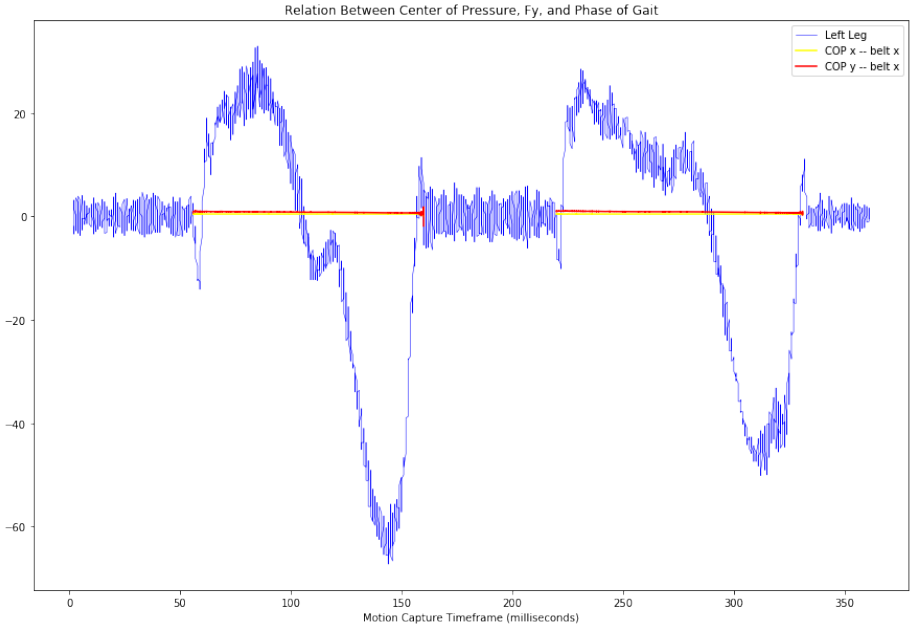

Figure 3.4: Center of Pressure Data Aggregated

Center of pressure is represented as two values the center of pressure exerted on the ground in the Xth plane and the Yth plane. Center of Pressure is calculated independently for each treadmill belt, resulting in four values describing the Xth and

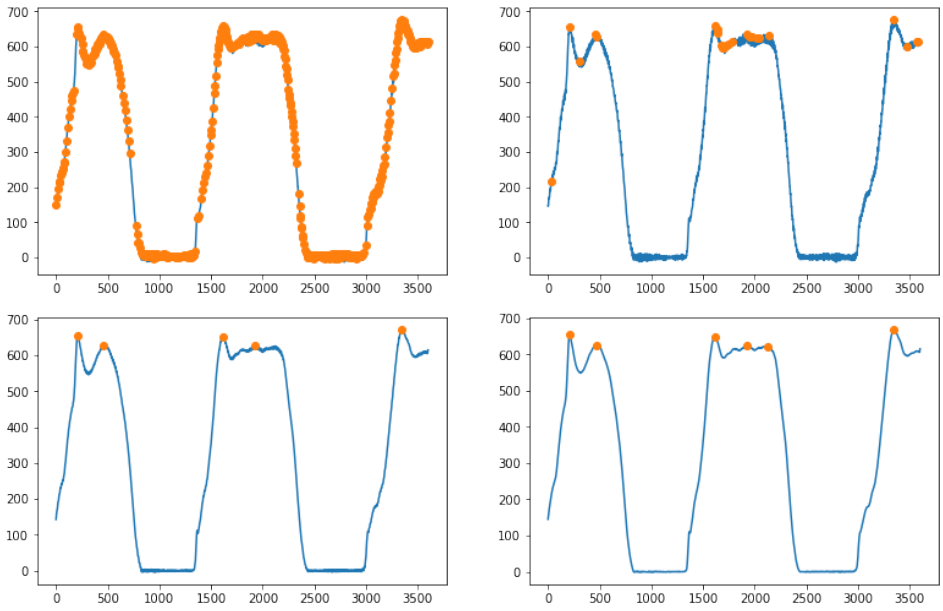

Figure 3.5: Identifying End of Unloading and Toe Off Events

Yth center of pressure for each the right and left belt of the treadmill. An image of the Bertec dual belt treadmill overlaid with the arrows showing each of the three planes in 3.2. For each line in the dataset, a center of pressure is calculated in each of these dimensions, described in the diagram 3.3.

A final and related step of preparing the Center of Pressure data, removing inaccurate Center of Pressure data, is depicted in 3.4. Previously, we calculated Center of Pressure for all tuples in the dataset. In this instance, we go back and remove the Center of Pressure information in the discussed portions of the gait where the leg is not in contact with the ground to avoid wrongly incorporating these values into later analysis.

The first objective in pre-processing was identifying the end of unloading and toe-off events based on the dataset. Depicted in the left plot in 3.5, we see that the noise in the dataset has caused many points to look like local maximum in the dataset, even after widening the width of the peak search (thus requiring a certain

number of points to occur between two identified peaks). To address this, signal processing is used to smooth out the noise and accurately identify only the major local maximum in the Fz force data, as shown in the right side plot of figure 4. In the bigger picture, identifying these points in the data gives us the ability to automate the identification of end of unloading and toe-off events. These are denoted as "H" for end of unloading, "T" for Toe-Off and M for Midstance. "End of unloading" describes when the weight has been touches the ground again after the swing phase of the gait cycle. This is synonymous with the initial contact phase shown in 2.1. The Final peak in the Fz (Vertical Force) is associated with Toe-Off; the moment the foot is taken out of contact with the ground, depicted as the "pre-swing" phase in 2.1 above. As suggested in the final plot of 3.5, Midstance may or may not be present in a particular gait cycle. In the selected segment below, we see both cases. For this reason, the code is written in a way to adapt to midstance data peaks, classifying them as M as to separate these moments from the end of unloading and toe-off events.

3.4 Implementation of Analysis

Analysis consists of two stages: statistical analysis of variables, and neural network creation for future data point prediction. Through statistical analysis, we aim to write a system that can compute medically used variables based on the work of Dr. Joe Verghese [60], highlighted previously 2.6. In the use of the neural network, we seek to predict future data values in the time series. All analysis is carried out using python. In particular, the following python packages are utilized: math, numpy, pandas, sklearn, matplotlib, scipy.signal, keras, and tensorflow. All data is saved and calculated results data are saved in CSV format. The formatting of this data has given us freedom to explore predictive metrics. In addition, since the original data remains

intact, the opportunity to retroactively analyze features and evolve algorithms over the course of the next five, ten or twenty years as more data and insights become available remains.

3.4.1 Statistical Analysis Specific Implementation

To prepare data for statistical analysis, the time leading up to end of unloading, and toe-off as well as the time following end of unloading and toe-off are denoted, so that features in these time periods can be compared later on in analysis.

3.4.2 Neural Network Specific Implementation

Data Preparation

To prepare data for processing in the neural network, the data is from time T, and previous times T-1, T-2 through T-"amount of history", as shown in 3.6. into a 2d matrix. The matrix is organized by the features, first - last, for each time, furthest in the past (T-"amount of history") through the current time "T". Finally, in time T, we remove all features except the one we are aiming to predict. In 3.6, we are predicting "COPx x". By removing the other data, we are insuring that only data from the past is being used to from a conclusion about the data in time T.

Environment

The neural network was trained on a 40–core Linux server. Training took an approximate 35-50 minutes per-epoch in total run time, though this varied with the parameters used.

Each datafile was 185.4 to 238.8 MB; this includes data collected at 1000 Hz off the belts of the force treadmill, EMG and motion capture data; equivalent to a

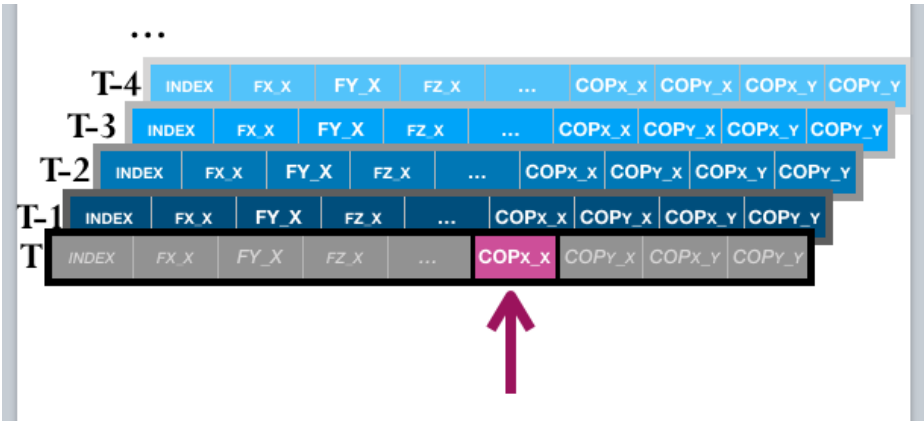

Figure 3.6: Data set up for neural network implementation

datapoint collected every 0.001 of a second. For training, 30 cycles of gait data were used. These file sizes are 30MB in size.

Network Architecture

Following the framework of previous work in temporal model building, the initial model was developing using a Long-Short Term Memory (LSTM) Network layer with a dropout and two fully connected layers on top. The LSTM layer contains 50 neurons, followed by a 0.5 dropout layer and two fully connected layers with 31 an 1 neurons respectively, as shown in 3.7.

Dropout layers have been shown to reduce over-fitting to data in noisy data, which was the primary draw to including such a layer [54, 11]. A dropout layer will randomly select a percentage of output values to not advance to further layers, as shown in 3.8. In this way, it is likely that the quickest learning neurons will randomly be blocked, resulting in other neurons receiving feedback necessary for improvement [54].

Activation Function: The hyperbolic tangent (TANH) activation function in Keras Python Deep Learning Package was selected for this project.

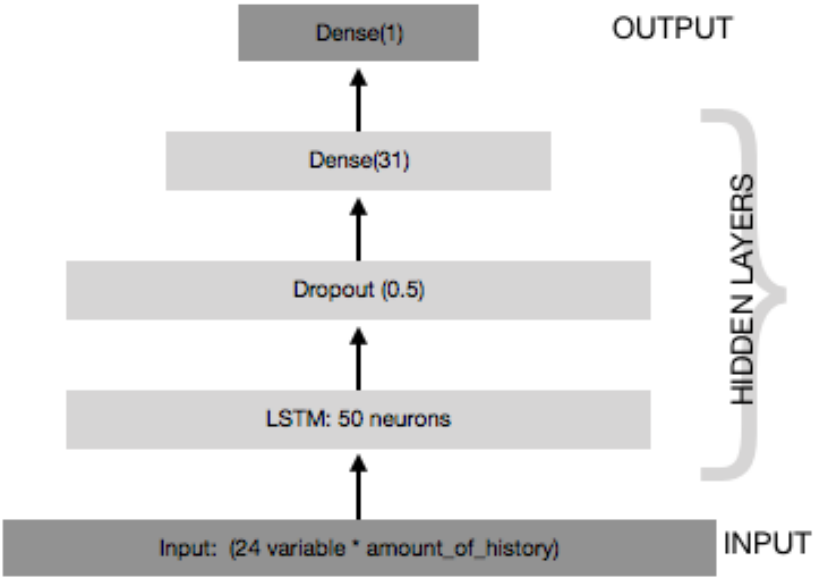

Figure 3.7: Neural Network Implementation

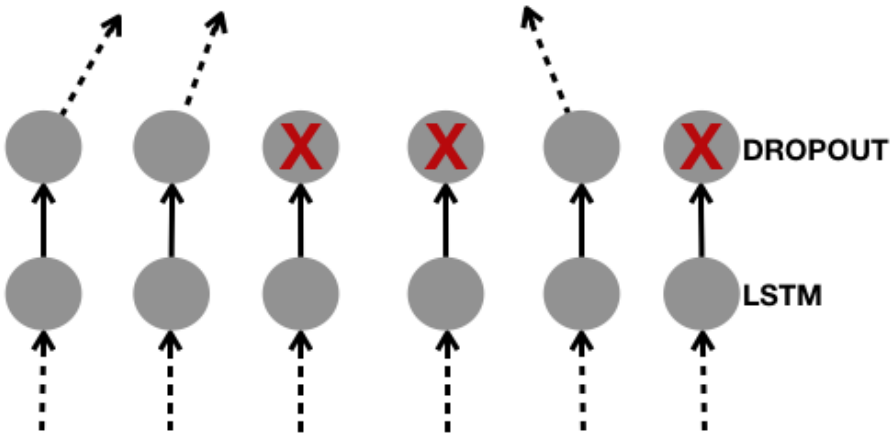

Figure 3.8: Dropout Layer

Mathematical expression:

$$tanh(z) = [exp(z) - exp(-z)]/[exp(z) + exp(-z)]$$

1st order derivative:

$$tanh'(z) = 1 - ([exp(z) - exp(-z)]/[exp(z) + exp(-z)])^2 = 1 - tanh^2(z)$$

Since the activation function represents a number from -1 to 1, either no flow, complete flow, or some partial flow of information through the gate is controlled in this way. Selecting a function, such as TANH, with a second derivative sustains for a long range before approaching to zero addresses the concern of vanishing gradients. TANH has been shown to converge faster in practice and the gradient computations have less associated cost [26].

In fitting our algorithm, the Mean Absolute Error (MAE) loss function is utilized, which calculates the average of the absolute difference between the actual and predicted values. The MAE loss is less susceptibility to outlying data points, as was thus chosen. The ADAM optimizer was used for complication and fitting the model, similarly for it's ability to handle data containing noisy gradients [27].

A timestep of 50 was selected; higher timesteps insure that long-term dependencies will be captured, however this has the trade of converging slower [26]. In this dataset due to the cyclical nature of gait, and how densely populated this dataset is (1000 samples per second), a higher timestep will help us gather the bigger trends from very fine, small-scaled data, but this again has to be balanced with the time constraints to get the model to converge.

The features passed into the neural network were the features from time T-1, T-2, T-3, through T-"length of history", as defined above in data preparation. A length of history of both 4 and 12 were experimentally considered.

Initially, 50 epochs were used for training. As additional parameters were finalized, the number of epochs was increased to 1000 to get a more refined and accurate model.

```
1  Layer Type                    Output Shape              Param #
2  =================================================================
3  lstm_1 (LSTM)                 (None, 50)                14800
4  _________________________________________________________________
5  dropout_1 (Dropout)           (None, 50)                0
6  _________________________________________________________________
7  dense_1 (Dense)               (None, 7)                 357
8  _________________________________________________________________
9  dense_2 (Dense)               (None, 1)                 8
10 =================================================================
11 Total params: 15,165
12 Trainable params: 15,165
13 Non-trainable params: 0
```

Listing 3.1: Initial Model

4 Results

4.1 Statistical Analysis: Variance of Metrics

Following from past research, our analysis starts with a consideration of stride length and a comparison of the amount of time spend in swing versus stance phases, shown in 4.1. From this, we see that our healthy user-study population follows the expected trends. In terms of stride length, we see in the left plot in figure 6 that the mean stride distance is comparable between the left and right legs. The variance is also comparable: 0.00171275 and 0.00828947 for left and right, respectively.

We also consider the average number of seconds spent in stance compared to swing phase. A typical distribution is 60:40, where 60 percent of the gait cycle is made up by the stance phase, and 40 percent of the gait cycle is made up by the swing phase. However, this is for a typical walking speed, and in this study, the speed was 0.5m/s, which is slower than a normal walking speed. This is shown in the left plot in 4.2. The average seconds of stance is 1.364951 per gait cycle; the variance of this measures is 0.006751. The average seconds of swing is 0.447762 with a variance of 0.003932. This equates to a distribution of 75:25, stance and stride respectively. There is a slight skew of stance downward and swing upward, mirroring the complementary nature of stance and swing. To this end, a shorter stance is correlated with a longer swing.

On this note, our data can also speak to cadence the average number of strides per seconds. A total stride which includes both stance and swing, is on average 1.813739. The total stride length has a variance of 0.006851. This is equivalence to a cadence

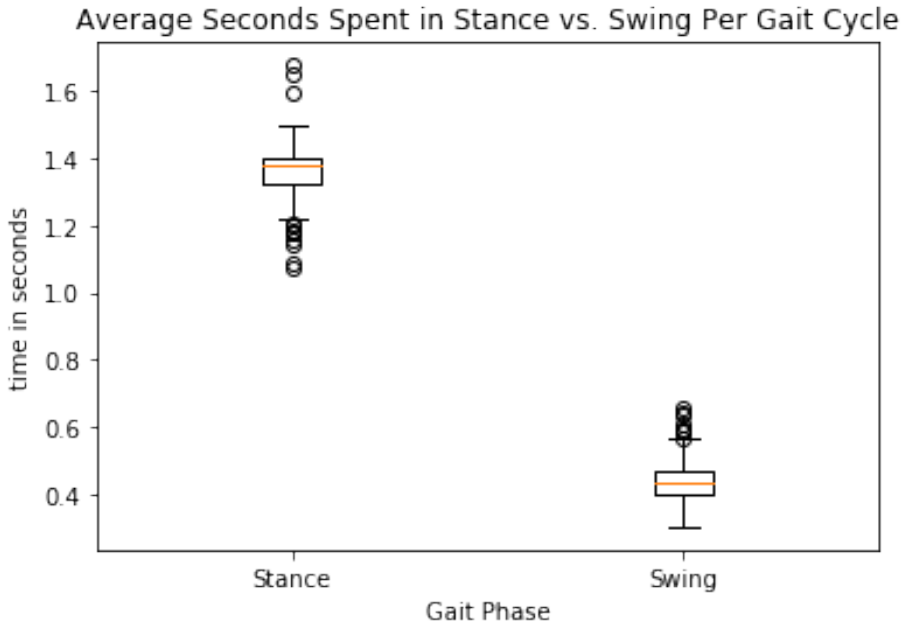

Figure 4.1: Street Length (meters)

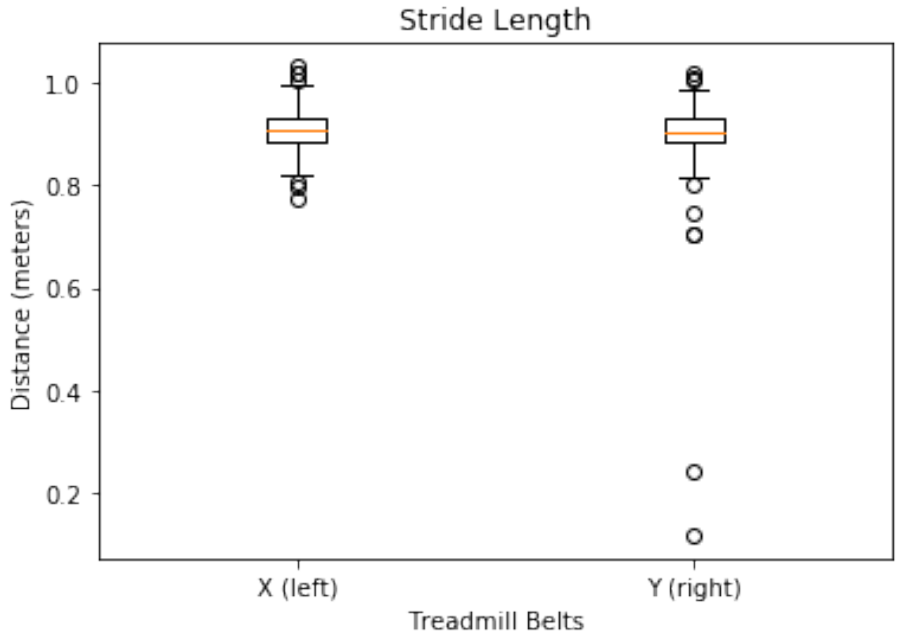

Figure 4.2: Average Stride vs. Stance Time within the Stride (seconds)

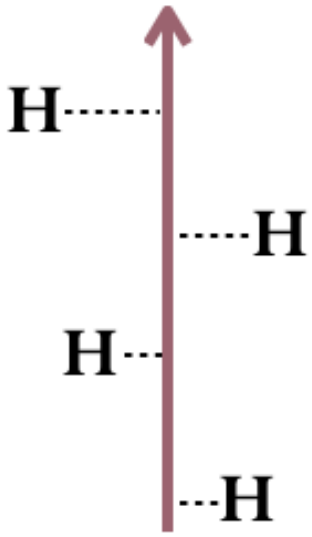

Figure 4.3: End of Unloading – Lateral Distance

of 33.080827 strides per minute.

Balance is also analyzed using the Center of pressure at the end of unloading. This shows the amount of lateral distance shift in each stride. We aggregate this value by identifying the end of unloading of one foot and compare it to the previous end of unloading of the opposite foot. A diagram of this concept is shown in 4.3 We do this separately for each foot. The average is 0.005424 and -0.005457 and the variance is 0.000494 and 0.000488 respectively for the left and right legs. What we see with this comparable mean and variance in 4.4, is a skewing tendency for the left leg to step slightly closer to the right, and the right to step slightly further from the left in comparison to the Center of Pressure of the previous end of unloading.

In addition to looking at the variance of lateral movement, we also propose a micro-look at Center of Pressure revolving around crucial moments in the gait cycles. Two sets of events are defined, and discussed below:

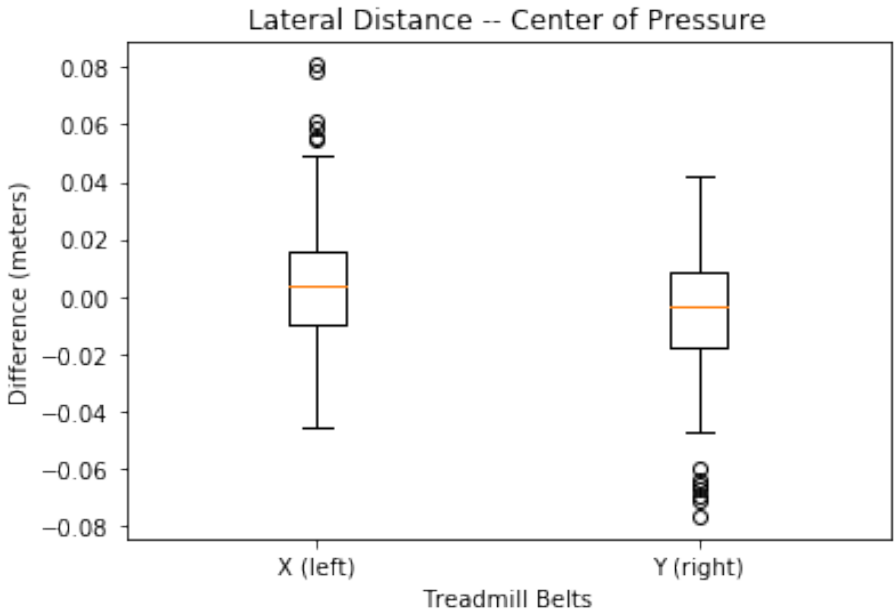

Figure 4.4: Analyzing Lateral Movement using Center of Pressure

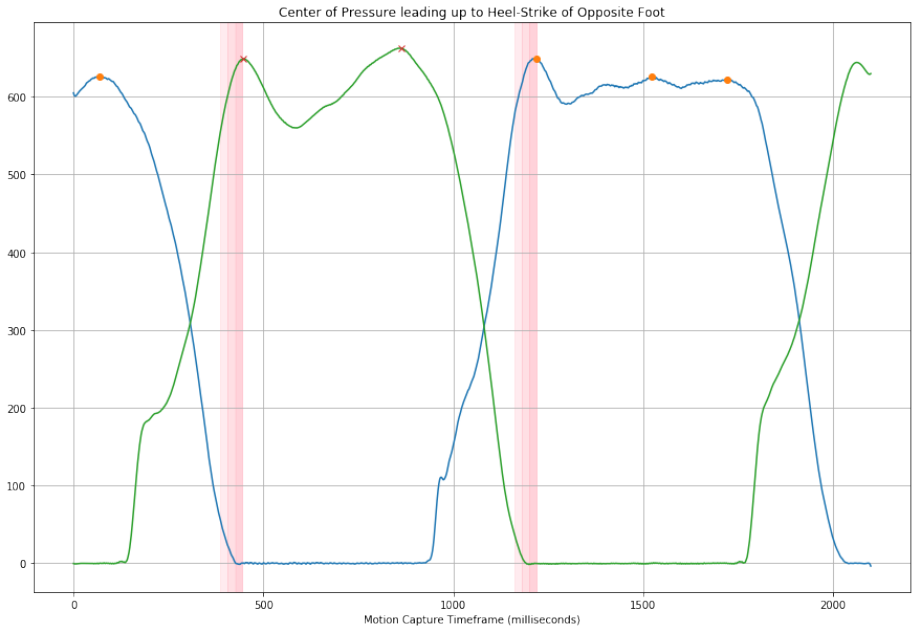

Figure 4.5: Time leading up to end of unloading, shown in increasingly strong colors of red respectively

Pairwise Comparison Between	Plane	Left Forceplate	Right Forceplate
End of Unloading and Midstance	X	P = 0.588390	P = 0.086498
End of Unloading and Toe-Off	X	P = 0.016210	P = 0.001724
Midstance and Toe-Off	X	P = 0.001346	P = 0.001346

Table 4.1: Comparison of Center of Pressure During End of Unloading, Midstance, and Toe-Off Events in the Gait Cycle, in the Xth center of pressure plane for each treadmill belt.

- Heel-Strike, Toe-Off, and Midstance (when present)
- Stride Length (cm)
- 60 to 40 milliseconds before Heel-Strike, 40 to 20 milliseconds before Heel-Strike, and 20 to 0 milliseconds before Heel-Strike, shown in increasing strengths of red respectively in 4.5

Heel-Strike, Toe-Off and Midstance are unique in that these are times when the forces plateau, and switch directions. Thus, these are also times when balance concerns may become more evident. To carry out these comparisons, we have computed P-values off the pairwise comparison of each combination of the two, as shown in 4.1. For the following comparisons, if the P-value is less than 0.05, we are highly confident that the distributions significantly differ, and can claim that the treatments had a significant impact on the measured value.

Based on the P-values shown in table 1, we can that toe-off is well distinguished from both heel-strike and midstance. Heel-strike and midstance in both cases, is above 0.05, so may not be significantly varied.

As discussed, heel-strike through the end of unloading is a time when balance changes significantly. To this end, we seek to evaluate balance in the time leading up to heel-strike using Center of Pressure in the medial-lateral (Xth) plane, shown in 4.2. Again, for the following comparisons, if the P-value is less than 0.05, we are highly

Pairwise Comparison Between	Plane	Left Forceplate	Right Forceplate
A and C	X	P = 3.6 e-41	P = 4.1 e-139
A and B	X	P = 2.1 e-10	P = 5.9 e-36
B and C	X	P = 1.7 e-18	P = 1.7 e-81

Table 4.2: Comparison of Center of Pressure in three timeframes leading up to end of unloading where A refers to the timeframe: 40 to 60 milliseconds before Heel-Strike; B refers to the timeframe: 20 to 40 milliseconds before Heel-Strike and C refers to the timeframe: 0 to 20 milliseconds before Heel-Strike

confident that the distributions significantly differ, and can claim that the treatments had a significant impact on the measured value.

4.2 Results From Neural Network

4.2.1 Signal Processing For Neural Network Predictions

As can be seen in 4.6, the model struggles to capture the shape of the data file. On the other hand, when we use a high amount of signal processing (window size of 179, polyorder of 7), we see in 4.7 that the prediction appears much more accurate. However, at this point, the data is so processed, that the shape of the data is highly removed from the original data. This is shown in 4.8. In this plot, we see that the blue line is the original data, the orange is a signal processed version or the original data (window size of 31, polyorder 7), and the magenta is the highly signal processed data (window size of 179, polyorder of 7) shown in 4.7. Note that after a more varied portion of data, the highly signal processed data (magenta) is slow to adjust to the flatter portions of data. This can be accounted for by the wider window size that incorporates a section of the varied part of data into the average of the flatter part of the data, thus altering the shape of the data in these areas. Because of this, the high amount of signal processing (window size of 179, polyorder of 7) does not seem fitting to describe this data.

As an final evaluation of both signal processed models, we look at building the model with each, and making predictions. The plots compare the original signal processed data with the estimated values. The results are shown in 4.9. However, we have computed the Root Squared Mean Errors (RSME) against the non-signal processed data to see how well the model fits the actual model.

In the case of the highly signal processed data (window size of 179, polyorder of 7), the RSME comparing these results to the non-signal processed original data was 1.38, though majority of the predictions were within the (-0.06 through 0.01 range). In the case of the moderately signal processed data (window size of 31, polyorder of

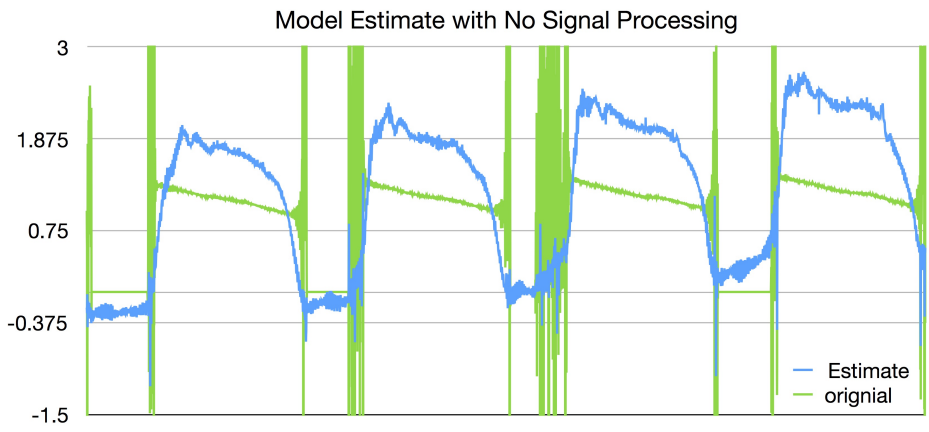

Figure 4.6: Initial Model Estimates with no signal processing

7), the RSME comparing these results to the non-signal processed original data was 1.22, though majority of the predictions were within the (-0.08 through 0.19 range). These ranges are also shown in 4.10, 4.11 and 4.12. As shown in these box plots, the higher signal processed data actually has more outlying points and a slightly wider range in terms of difference from predicted and actual value, as compared to the data signal processed with a smaller window size (window size 31, polyorder 7).

As an aside, once the signal processing has been set, it was decided to compare between the signal processed original and the estimate, as the signal processed original controls some of the noise, which will inevitably reduce some of the error. Additionally, the signal processing was selected for it's ability to both capture the shape and essence of the data without the complexity that the non-altered signal contains, and is thus used for comparing in these models.

4.2.2 Batch Size Considerations

At this point, only the signal processing with window size of 31 and polyorder of 7 will be used from this point forward. The next feature to be tuned is the batch size. After multiple runs of the model, a batch size of 75 was selected. The results

Figure 4.7: Initial Model Estimates with high levels (179,7) of signal processing

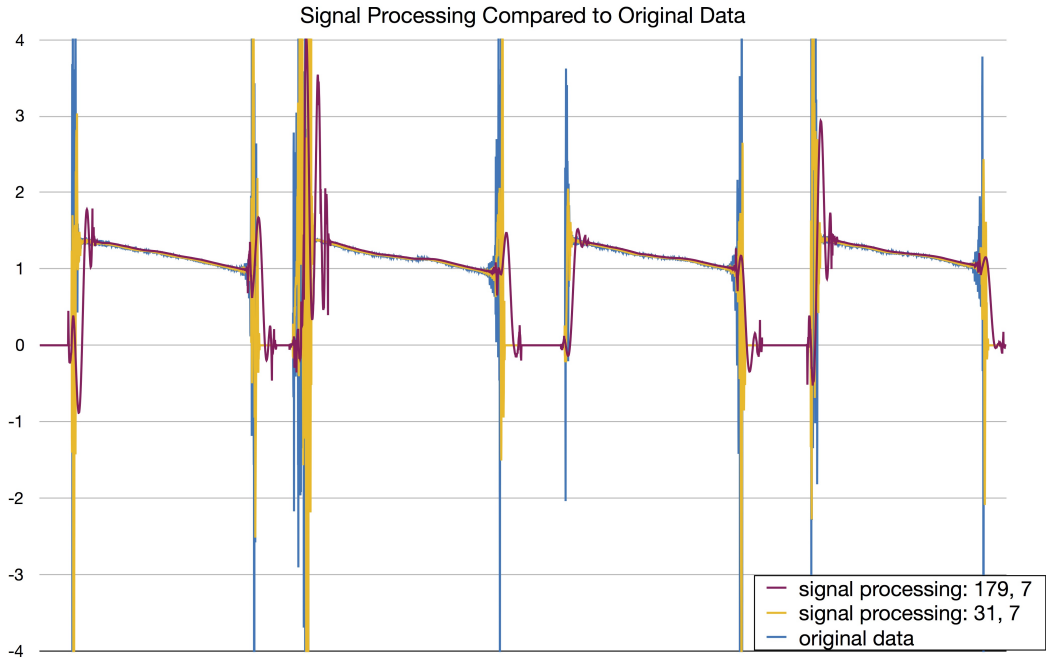

Figure 4.8: Comparison of Signal Processing Signals with Original

from this can be seen in 4.14, as well as contrasting results from a model built with a batch size of only 4 for comparison in 4.13. For comparison, the RSME of these models' predictions compared to the signal processed original data is 0.497 and 0.66 respectively. The batch size defines the number of training examples that occur before back-propagation. Typically networks train faster with batches as the weights

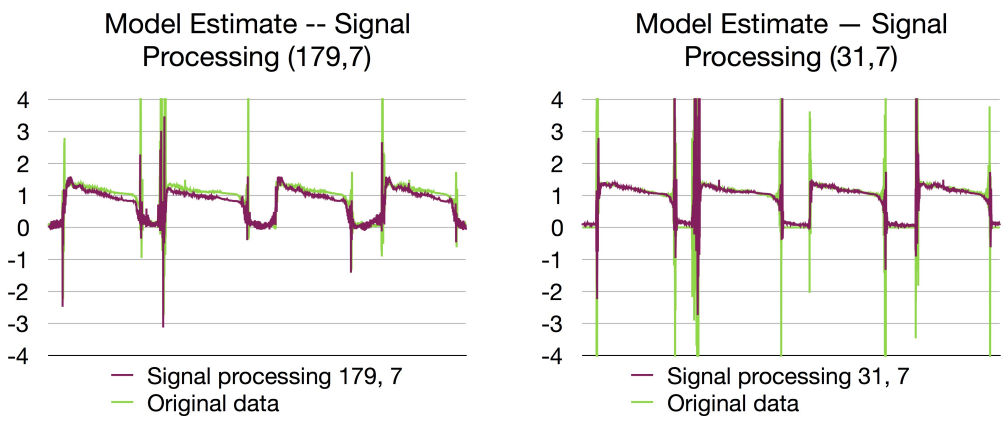

Figure 4.9: Tuned Signal Processing

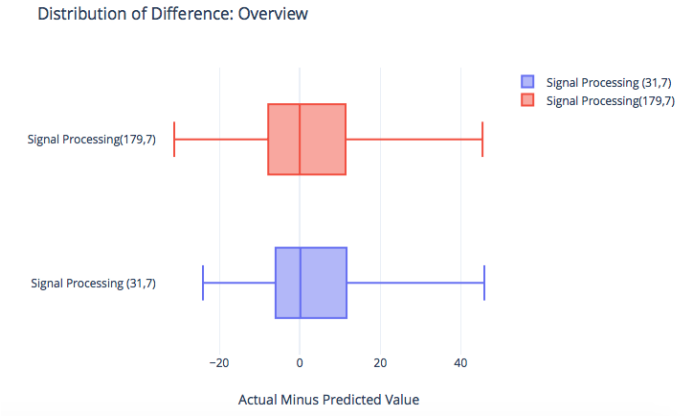

Figure 4.10: Distribution of Differences – Overview

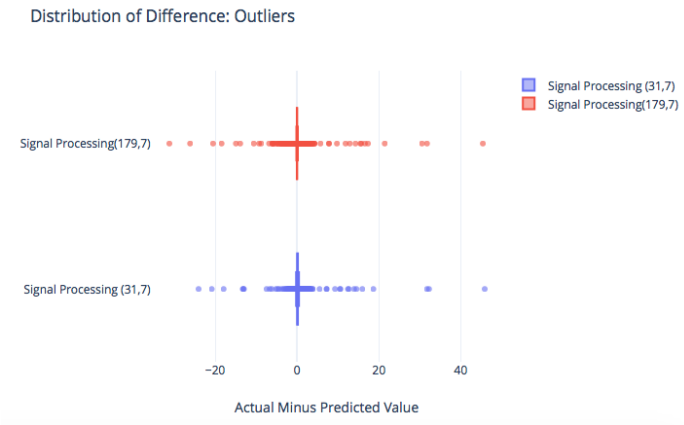

Figure 4.11: Distribution of Differences – Outlying Points

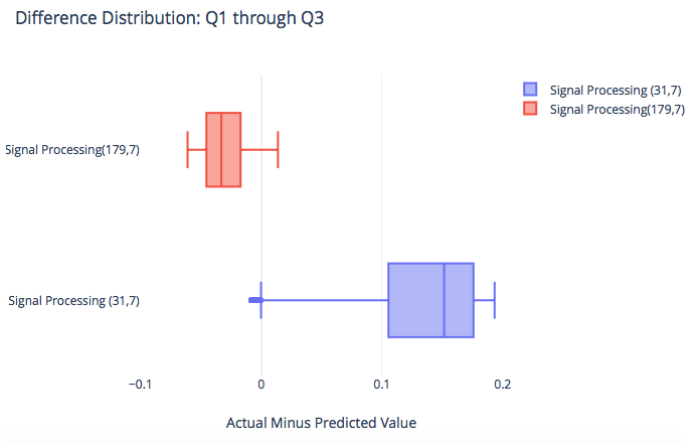

Figure 4.12: Distribution of Differences Between Q1 and Q3

between nodes get updated after each propagation. In contrast if all the samples are used during propagation, only one update would be made. An important comment being that large batch sizes require more memory space to process. This becomes a balancing act, as batch sizes too small in size lead to less accurate estimates.

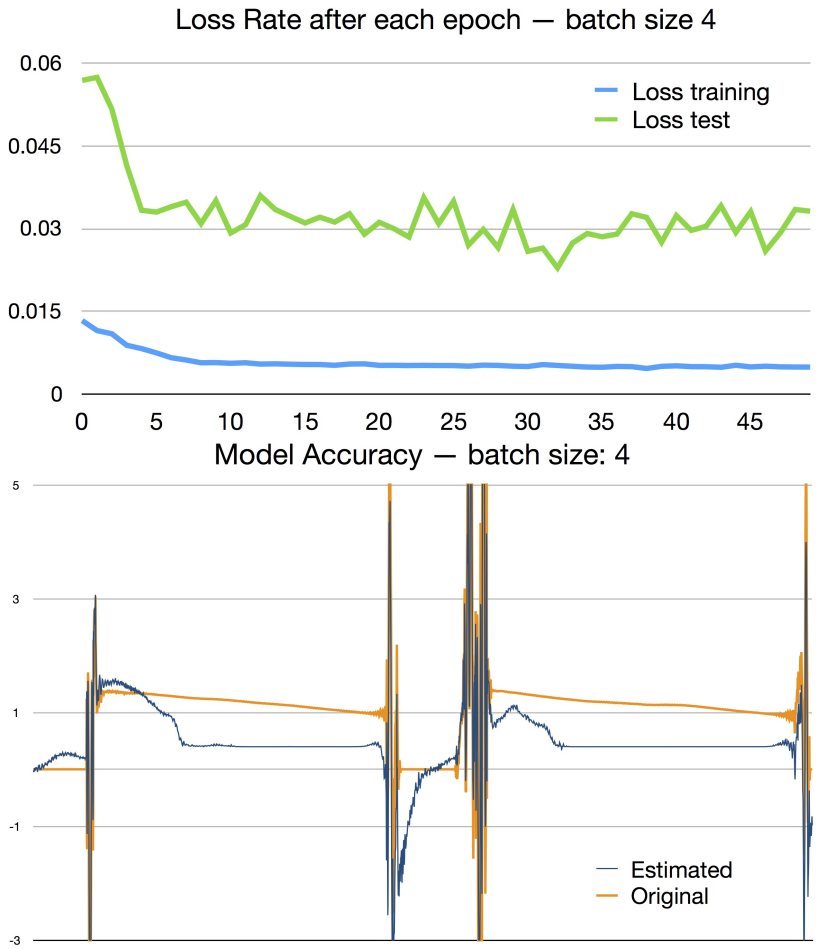

Figure 4.13: Model Loss and Estimation with Batch Size 75

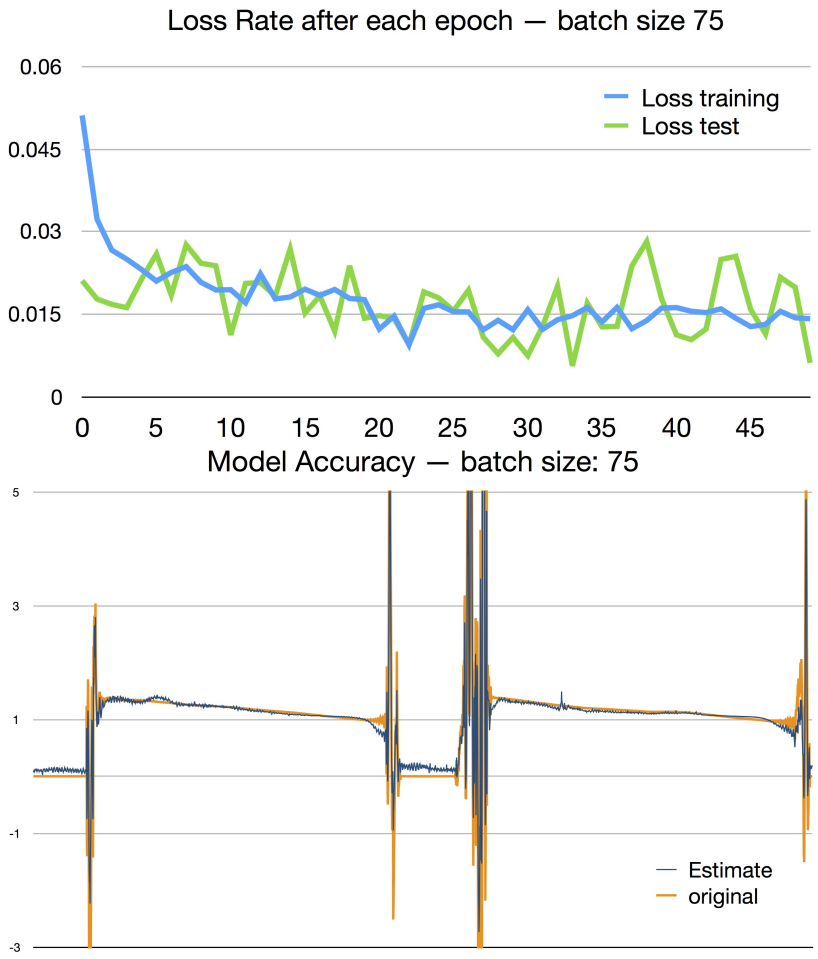

Figure 4.14: Model Loss and Estimation with Batch Size 75

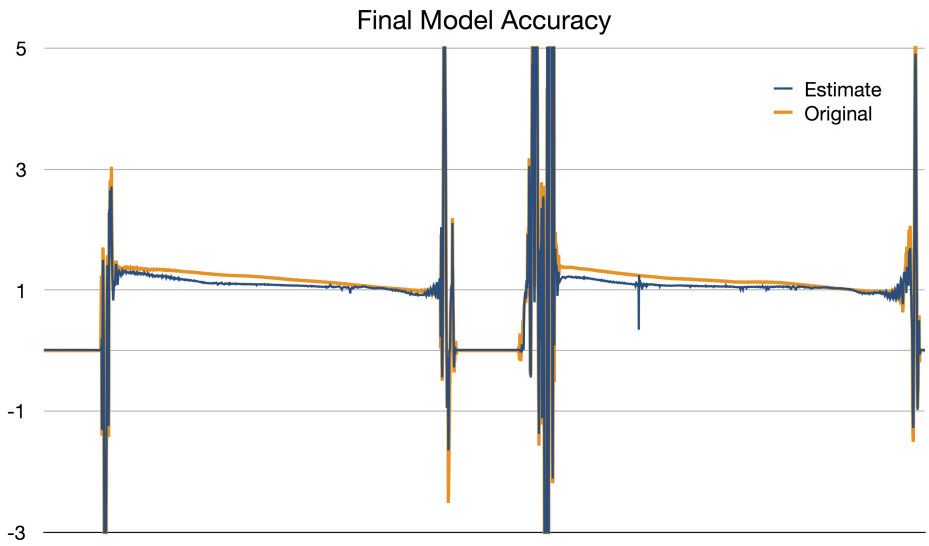

Figure 4.15: Initial Model Estimates with no signal processing

4.2.3 Increasing Training Epoches

The final step was training the model on 1000 epoches as opposed to the previously used 50 epoches. This resulted in a final RMSE of 0.231 and is depicted in 4.15 and 4.16.

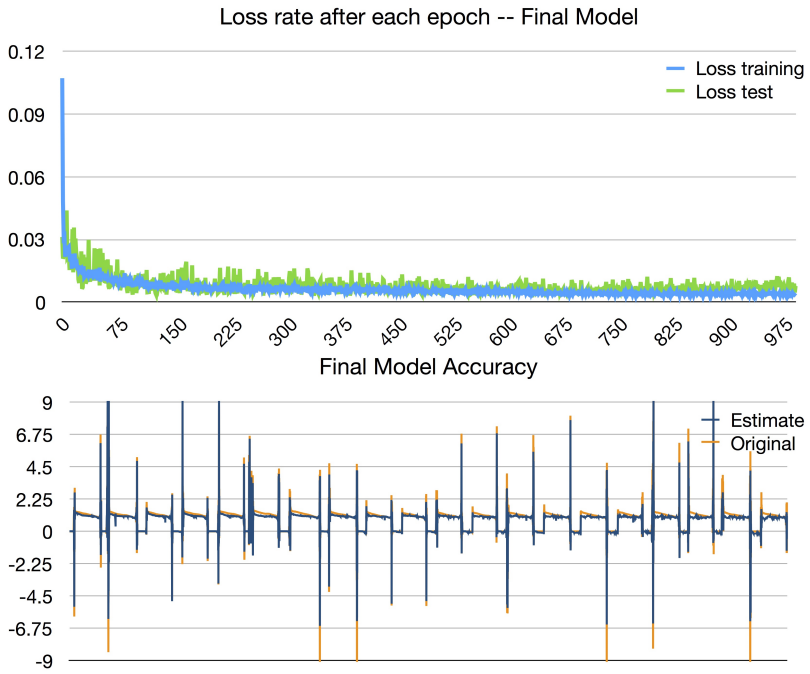

Figure 4.16: Model Loss and Estimation with Batch Size 75

5 Conclusions

In this project, we have algorithmically: (1) extracted features of gait, (2) analyze variation in particular features of gait and (3) explore the use of multivariate neural network models in Center of Pressure. We provide an exploratory example of how gait patterns can be evaluated and predicted through modeling on a single participant basis.

Future work is considered in two primary areas: data collection process and model improvements.

In terms of the data collection process, the following considerations have been discussed: (1) incorporating EMG data into model building and analysis of balance and (2) consider the incorporating cognitive tasks into the data collection process. Previous research supports that these factors may be likely correlated. In terms of EMG, data was collected, so this becomes a matter of analysis. In terms of cognition data, a new study protocol would have to be developed to incorporate that into the current design.

As we consider the model design, we are primarily looking to predict further in advance than one time-step. To do this, we propose modifying the current Center-of-Pressure model to predict other features of gait. As long as we have information on the force and moments, we can generate COP predictions off of this into the future, creating an auto-generated signal. To this end, we hope to further extend the current model to enable and test the accuracy of predictions beyond one time-step. As we think about this, we consider how many variables we would have to model and predict.

To speed up this process, we also plan to evaluate the dependency on each variable by the model, to possibly limit the variables used to build the model. To evaluate this, we will build the model with and without combinations of the variables based on the weightings of the particular variables in the model.

Outside of specifics of the model design, we also consider future use of this system within the realm of Vascular Dementia. While designed with a focus on prediction of Vascular Dementia, we consider the possibility of using such a model as an ongoing evaluation metric for a population currently effected by dementia.

The effects of vascular dementia are far reaching. The uniqueness of our approach is the application of computational analysis along with a the focused on developing a personalized understanding of gait. Several research studies have identified gait as an important marker in early identification of vascular dementia [49, 58].

We are proposing a tool that advances the use of gait metrics for early prediction and recognition of subcortical vascular dementia and vascular cognitive impairment. In this research, and work to come, the challenge of differentiating vascular dementia from other forms of dementia and effects of aging remains a significant challenge. By continuing to explore data aggregation and metric evaluation in the realm of gait, we aim to contribute to this challenge of differentiating onset patterns from the trajectory of aging. Future work in progress looks at implementing advanced classification techniques to recognize shifts in patterns; incorporating other early indicators of subcortical vascular dementia into the tool such as measures of cognitive abilities, executive function, management of multiple tasks, and additional physiological measures; and providing real-time feedback features to participants; all with the goal of better understanding the physiological and biomechanical control loss that occurs during Vascular Dementia onset.

A Appendix A

This appendix contains computationally-focused files and a brief description of the files' functionality.

A.1 Calculate Aggregate Values

This program computes aggregate values including:

- center of gravity
- heel-strike and toe-off events
- phase mark

separately for each forceplate. These aggregate values are used later in analysis.

```
1  import pandas as pd
2  import matplotlib.pyplot as plt
3  import statistics
4  from scipy.signal import find_peaks
5  from scipy.signal import savgol_filter
6
7  X = pd.read_csv('NEW_GOOD.csv')
8
9  X['COPx_x'] = 0
10 X['COPy_x'] = 0
11 X['COPx_y'] = 0
```

```
12 X['COPy_y'] = 0
13 X['phase_mark'] = 0
14 print(list(X.columns.values))
15
16 #### Xcp = -My/Fz.
17 #### Ycp = Mx/Fz.
18
19 X['COPx_x'] = -X['my_x']/X['fz_x']
20 X['COPy_x'] = X['mx_x']/X['fz_x']
21 X['COPx_y'] = -X['my_y']/X['fz_y']
22 X['COPy_y'] = X['mx_y']/X['fz_y']
23
24 dark_sage = (.1254,.2784,0.2078)
25 mediumer_sage = (0,0,0)
26 medium_sage = (0,0,0)
27 light_sage = (0.5450, 0.6078, .4784)
28 lighter_sage = (0.70588, 0.74901, 0.662745)
29
30 dark_mauve = (0.3568,0.3294,0.37647)
31 mediumer_mauve = (0,0,0)
32 medium_mauve = (0,0,0)
33 light_mauve = (0.6078, 0.5764, 0.6274)
34 lighter_mauve = (0.72549, 0.701960, 0.73725)
35
36 mustard = (0.854801, 0.717647, 0.243137)
37 dusty_rose = (0.76078, 0.5098, 0.52156)
38
39 plot_me = X.iloc[3100:6600]
40
41 avg_before = 0
42 avg_after = 0
```

```
43
44 for pointer, row in plot_me.iterrows():
45     before = pointer - 10
46     after = pointer + 10
47     if before < 0:
48         before = 0
49     if after > plot_me.tail(1).index.item():
50         after = plot_me.tail(1).index.item()
51
52     #print(pointer, after) ##error handleing
53     avg_before = plot_me["COPx_x"].loc[before:pointer].mean()
54     avg_after = plot_me["COPx_x"].loc[pointer:after].mean()
55     difference = abs(avg_before - avg_after)
56     if difference > .1:
57         ##df.at[i,'ifor'] = ifor_val    where i is index (pointer) and
58         plot_me.at[pointer,'phase_mark'] = 50
59         #print("***")
60     avg_before = plot_me["COPx_y"].loc[before:pointer].mean()
61     avg_after = plot_me["COPx_y"].loc[pointer:after].mean()
62     difference = abs(avg_before - avg_after)
63     if difference > .1:
64         ##df.at[i,'ifor'] = ifor_val    where i is index (pointer) and
65         plot_me.at[pointer,'phase_mark'] = -50
66         #print("***")
67     #print (str(pointer) + "......." + str(difference) + "\n"+ str(
           before) + "---" + str(after) + "......." + str(avg_before) +
           "---" + str(avg_after) + "\n\n")
68
69     #print(plot_me['phase_mark'])
70 for pointer, row in plot_me.iterrows():
71     before = pointer - 30
```

```
72      after = pointer + 30
73      beforetight = pointer - 5
74      aftertight = pointer + 5
75      if before < 0:
76          before = 0
77      if after > plot_me.tail(1).index.item():
78          after = plot_me.tail(1).index.item()
79
80      #print(pointer, after) ##error handling
81      avg_before_tight = plot_me["phase_mark"].loc[beforetight:pointer].
            mean()
82      avg_after_tight = plot_me["phase_mark"].loc[pointer:aftertight].mean
            ()
83
84      all_average = plot_me["phase_mark"].loc[before:after].mean()
85      #difference = abs(avg_before - avg_after)
86      if all_average > 25 or avg_after_tight > 25:
87          ##df.at[i,'ifor'] = ifor_val   where i is index (pointer) and
88          plot_me.at[pointer,'phase_mark'] = 50
89      if all_average < -25 or avg_after_tight < -25:
90          ##df.at[i,'ifor'] = ifor_val   where i is index (pointer) and
91          plot_me.at[pointer,'phase_mark'] = -50
92
93      for count, item in plot_me.iterrows():
94          if item['phase_mark'] == 50:  #x treadmill belt
95              plot_me.at[count,"COPx_x"] = np.NaN
96              plot_me.at[count,"COPy_x"] = np.NaN
97          if item['phase_mark'] == -50: #y treadmill belt
98
99              plot_me.at[count, "COPx_y"] = np.NaN
100             plot_me.at[count, "COPy_y"] = np.NaN
```

```
101
102     yhat1 = savgol_filter(plot_me['fz_y'], 101, 7) # original -- window
            size 51, polynomial order 3
103
104     #plt.plot(plot_me['fz_x'])
105     plt.plot(yhat1)
106     peaks1, _ = find_peaks(yhat1,height=400, distance = 100, width=50)
107     plt.plot(peaks1, yhat1[peaks1], "o")
108     plt.figure(figsize=(15,10))
109     #plt.plot(np.zeros_like(plot_me['fz_x']), "--", color="gray")
110     plt.show()
111
112     ##saves the peaks column into the "local max x" column of the
            dataset
113     print(peaks1)
114     plot_me['local_MAX_y'] = 0
115     for index, row in plot_me.iterrows():
116         if index in peaks1:
117             plot_me.loc[index,'local_MAX_y'] = 1
118
119     print(max(plot_me['local_MAX_y']))
120     print(sum(plot_me['local_MAX_y']))
121
122     yhat2 = savgol_filter(plot_me['fz_x'], 101, 7) # original -- window
            size 51, polynomial order 3
123
124     #plt.plot(plot_me['fz_x'])
125     plt.plot(yhat2)
126     peaks2, _ = find_peaks(yhat2,height=400, distance = 100, width=50)
127     plt.plot(peaks2, yhat2[peaks2], "x")
128     plt.figure(figsize=(15,10))
```

```
129     #plt.plot(np.zeros_like(plot_me['fz_x']), "--", color="gray")
130     plt.show()
131
132     ##saves the peaks column into the "local max x" column of the
            dataset
133     print(peaks2)
134     plot_me['local_MAX_x'] = 0
135     for index, row in plot_me.iterrows():
136         if index in peaks2:
137             plot_me.loc[index,'local_MAX_x'] = 1
138
139     print(max(plot_me['local_MAX_x']))
140     print(sum(plot_me['local_MAX_x']))
141
142     plot_me['Single/Dual'] = "D"
143     plot_me['Left/Right'] = ""
144     for index, item in plot_me.iterrows():
145         if item['phase_mark'] != 0:
146             plot_me.at[index,'Single/Dual'] = "S"
147             if item['phase_mark'] == 50:
148                 plot_me.at[index,'Left/Right'] = "R"
149             else:
150                 plot_me.at[index,'Left/Right'] = "L"
151
152     X['Heel/Toe_x'] = ""
153     X['Heel/Toe_y'] = ""
154
155     startX = 0
156     startY = 0
157
158     for index, item in plot_me.iterrows():
```

```
159         if startX == 0 and item['local_MAX_x'] != 0:
160             startX = startX + 1
161             plot_me.at[index,'Heel/Toe_x'] = "H"
162         elif item['local_MAX_x'] != 0:
163             startX = startX + 1
164             plot_me.at[index,'Heel/Toe_x'] = "X"
165 
166         if item['fz_x'] < 100:
167             startX = 0
168 
169         if startY == 0 and item['local_MAX_y'] != 0:
170             startY = startY + 1
171             plot_me.at[index,'Heel/Toe_y'] = "H"
172         elif item['local_MAX_y'] != 0:
173             startX = startY + 1
174             plot_me.at[index,'Heel/Toe_y'] = "X"
175 
176         if item['fz_y'] < 100:
177             startY = 0
178 
179     print(sum(plot_me['local_MAX_x']))
180     print(sum(plot_me['local_MAX_y']))
181 
182     print(plot_me.groupby('Heel/Toe_y').size())
183     print(plot_me.groupby('Heel/Toe_x').size())
184 
185     X.to_csv("NEW_GOOD.csv", index=False)  ###this is where you output
        the new and pretty file
```

Listing A.1: Calculate aggregate values

A.2 conduct ANOVA

This program defines treatments groups and compares these treatment groups using P-value and one way ANOVA tests.

```
1  import  csv
2  import pandas as pd
3  import numpy as np
4  from scipy import stats
5
6  data = pd.read_csv('cleaned_data.csv')
7  data
8
9  ##########################################. CD3 vs CD2 cs CD1 on the X
       forceplate
10 treatment1 = data[data["Heel/Toe_y"] == "cd3"]["COPy_x"]
11 treatment2 = data[data["Heel/Toe_y"] == "cd2"]["COPy_x"]
12 treatment3 = data[data["Heel/Toe_y"] == "cd1"]["COPy_x"]
13
14 treatment4 = data[data["Heel/Toe_x"] == "cd3"]["COPy_y"]
15 treatment5 = data[data["Heel/Toe_x"] == "cd2"]["COPy_y"]
16 treatment6 = data[data["Heel/Toe_x"] == "cd1"]["COPy_y"]
17
18 f_val, p_val = stats.f_oneway(treatment1, treatment2, treatment3)
19
20 print("One-way ANOVA P =", p_val)
21 print(p_val)
22 print("        If P > 0.05, we can claim with high confidence that the
       means of the \n        results of all three experiments are not
       significantly different.")
23
24 z_stat, p_val = stats.ranksums(treatment1, treatment2)
```

```
25 print("MWW RankSum P for treatments 1 and 2 =", p_val)
26 z_stat, p_val = stats.ranksums(treatment2, treatment3)
27 print("MWW RankSum P for treatments 2 and 3 =", p_val)
28 z_stat, p_val = stats.ranksums(treatment1, treatment3)
29 print("MWW RankSum P for treatments 1 and 3 =", p_val)
30 print("        If P <= 0.05, we are highly confident that the
   distributions significantly \n        differ, and can claim that the
    treatments had a \n        significant impact on the measured value
   .")
31 #print(treatment1)
32
33 print("****************************************")
34
35 f_val, p_val = stats.f_oneway(treatment4, treatment5, treatment6)
36
37 print("One-way ANOVA P =", p_val)
38 print(p_val)
39 print("        If P > 0.05, we can claim with high confidence that the
   means of the \n        results of all three experiments are not
   significantly different.")
40
41 z_stat, p_val = stats.ranksums(treatment4, treatment5)
42 print("MWW RankSum P for treatments 4 and 5 =", p_val)
43 z_stat, p_val = stats.ranksums(treatment5, treatment6)
44 print("MWW RankSum P for treatments 5 and 6 =", p_val)
45 z_stat, p_val = stats.ranksums(treatment1, treatment3)
46 print("MWW RankSum P for treatments 4 and 6 =", p_val)
47 print("        If P <= 0.05, we are highly confident that the
   distributions significantly \n        differ, and can claim that the
    treatments had a \n        significant impact on the measured value
   .")
```

```
48
49
50 print("****************************************")
51
52 z_stat, p_val = stats.ranksums(treatment1, treatment4)
53 print("MWW RankSum P for treatments 1 and 4 =", p_val)
54 z_stat, p_val = stats.ranksums(treatment2, treatment5)
55 print("MWW RankSum P for treatments 2 and 5 =", p_val)
56 z_stat, p_val = stats.ranksums(treatment3, treatment6)
57 print("MWW RankSum P for treatments 3 and 6 =", p_val)
58 print("        If P <= 0.05, we are highly confident that the
    distributions significantly \n        differ, and can claim that the
     treatments had a \n        significant impact on the measured value
    .")
```

Listing A.2: ANOVA Example

A.3 Sub-partitioning

This program creates a sub-directory containing all the gait-cycles in the noted file (data) broken down into many smaller CSV files, each three gait-cycles (heel-strike to heel-strike) in length. Gait was also sub-partitioned into files each containing 30 gait cycles, and single gait cycles.

```
1  import pandas as pd
2  data = pd.read_csv('NEW_GOOD.csv')
3  counter = 0
4  start = 0
5  end = 0
6  for index, row in data.iterrows():
7          if row["Heel/Toe_x"] is "H":
8                  if start == 0:
9                          print("first start value")
10                         start = index
11                 elif counter % 3 == 0:
12                         end = index
13                         newdataframe = data[start:end]
14                         string = "threes/example" + str(counter) + ".csv
                               "
15                         print( str(start) + "      " + str(end) )
16                         newdataframe.to_csv(string, index=False)
17                         print("ping!    " + str(counter))
18                         counter = counter + 1
19                         start = index
20       else:
21           counter = counter + 1
```

Listing A.3: Sub-Partitioning Data

A.4 LSTM Network

This is an adaptation of the program originally discussed by Jason Brownlee (https://github.com/jbrownlee) on "Machine Learning Mastery" [5].

```
1  from math import sqrt
2  import numpy as np
3  from numpy import concatenate
4  from matplotlib import pyplot
5  from pandas import read_csv
6  from pandas import DataFrame
7  from pandas import concat
8  from sklearn.preprocessing import MinMaxScaler
9  from sklearn.preprocessing import LabelEncoder
10 from sklearn.metrics import mean_squared_error
11 from keras.models import Sequential
12 from keras.layers import Dense
13 from keras.layers import LSTM
14 from scipy.signal import find_peaks
15 from scipy.signal import savgol_filter
16
17 # convert series to supervised learning
18 def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
19     n_vars = 1 if type(data) is list else data.shape[1]
20     df = DataFrame(data)
21     cols, names = list(), list()
22
23         # input sequence (t-n, ... t-1)
24     for i in range(n_in, 0, -1):
25         cols.append(df.shift(i))
26         names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
27
```

```
28      # forecast sequence (t, t+1, ... t+n)
29      for i in range(0, n_out):
30          cols.append(df.shift(-i))
31          if i == 0:
32              names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
33          else:
34              names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
35
36      # put it all together
37      agg = concat(cols, axis=1)
38      agg.columns = names
39      # drop rows with NaN values
40      if dropnan:
41          agg.dropna(inplace=True)
42      return agg
43
44  #***************** load dataset ***************************
45  ##dataset = read_csv('thirties/example150.csv', header=0, index_col =
        False) ##, index_col="deviceframe")
46  ##dataset = read_csv('new_cleaned_v3_april9_2019.csv', header=0,
        index_col=False)
47  dataset = read_csv('threes/example18.csv', header=0, index_col=False)
48
49
50
51  dataset = dataset.drop(['phase_mark', 'local_MAX_y', 'local_MAX_x', '
        Single/Dual', 'Left/Right', 'Heel/Toe_x', 'Heel/Toe_y'], axis = 1)
52  dataset = dataset.drop(['deviceframe',"mocapframe_x","mocaptime_x"],
        axis = 1)
53  dataset = dataset.drop(['mocapframe', 'mocaptime', 'dev1/ai0', 'dev1/ai1
        ', 'dev1/ai2', 'dev1/ai3','dev1/ai4', 'dev1/ai5', 'dev1/ai6', 'dev1/
```

```
    ai7', 'dev1/ai16', 'dev1/ai17','dev1/ai18', 'dev1/ai19'], axis = 1)
54
55 dataset = dataset.reset_index()
56
57 print(dataset.head(5))
58
59 ##signal processing for all the COP values?
60 dataset['COPx_x'] = savgol_filter(dataset['COPx_x'], 179, 7)
61 dataset['COPx_y'] = savgol_filter(dataset['COPx_y'], 179, 7)
62 dataset['COPy_x'] = savgol_filter(dataset['COPy_x'], 179, 7)
63 dataset['COPy_y'] = savgol_filter(dataset['COPy_y'], 179, 7)
64
65
66 print(dataset.columns.values)
67 dataset.dropna(inplace=True)
68 indices_to_keep = ~dataset.isin([np.nan, np.inf, -np.inf]).any(1)
69
70 # summarize first 5 rows
71 print(dataset.head(5))
72
73 values = dataset.values
74
75 # integer encode direction
76 #encoder = LabelEncoder()
77 #values[:,19] = encoder.fit_transform(values[:,19])
78
79 # ensure all data is float
80 values = values.astype('float32')
81 # normalize features
82 scaler = MinMaxScaler(feature_range=(-1, 1))
83 scaled = scaler.fit_transform(values) ##********************I changed
```

```
    this
# specify the number of lag hours
n_hours = 3 ### lag -- how far back we will look (for example t-3, t-2,
    t-1, t of lag == 3)
n_features = 23  ### number of columns in the dataset
# frame as supervised learning
reframed = series_to_supervised(scaled, n_hours, 1)

##right here -- drop the columns that we don't want to predict
reframed.drop(reframed.columns
    [[69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91]],
     axis=1, inplace=True)

print(reframed.shape)

# split into train and test sets
values = reframed.values

training_split = int(len(dataset)/3)

##print(training_split)
##print(len(values))

train = values[:training_split, :]
test = values[training_split:, :]

# split into input and outputs
n_obs = n_hours * n_features

print(str(n_hours) + "  " + str(n_features) + "  " +  str(n_obs))

```

```
111 train_X, train_y = train[:, :n_obs], train[:, -1]
112 test_X, test_y = test[:, :n_obs], test[:, -1]
113 print(train_X.shape, len(train_X), train_y.shape)
114
115 print(test_X)
116 print(test_y)
117
118 # reshape input to be 3D [samples, timesteps, features]
119 train_X = train_X.reshape((train_X.shape[0], n_hours, n_features))
120 test_X = test_X.reshape((test_X.shape[0], n_hours, n_features))
121 print(train_X.shape, train_y.shape, test_X.shape, test_y.shape)
122
123 # design network
124 model = Sequential()
125 model.add(LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2]))) #
      ##timestamp -- long term dependencies, slower convergence
126 model.add(Dense(31))
127 model.add(Dense(9))
128 model.add(Dense(1))
129 model.compile(loss='mae', optimizer='adam')
130 # fit network
131 history = model.fit(train_X, train_y, epochs=50, batch_size=75,
      validation_data=(test_X, test_y), verbose=2, shuffle=False)
132
133 # plot history
134 #pyplot.plot(history.history['loss'], label='train')
135 #pyplot.plot(history.history['val_loss'], label='test')
136 #pyplot.legend()
137 #pyplot.show()
138
139 # make a prediction
```

```
yhat = model.predict(test_X)
test_X = test_X.reshape((test_X.shape[0], n_hours*n_features))
#test_X = test_X.reshape((test_X.shape[0], n_hours*n_features))


###historic data on the training #########
print(history.history)

df_history = DataFrame.from_dict(history.history, orient="index")
#export = df_history.T
df_history.to_csv("test_history.csv", index=False)

print(yhat)
print(test_y)

#rmse = sqrt(mean_squared_error(test_y, yhat))
#print('Test RMSE: %.3f' % rmse)

#export2 = DataFrame([test_y, yhat]).T
#export2.to_csv("test2.csv", index=False)
print("********")
#print(test_X[:,-36:])
#print(test_X.shape)
##print(scaler.transform(yhat))

# invert scaling for forecast
inv_yhat = concatenate((test_X[:,-22:], yhat), axis=1)
inv_yhat = scaler.inverse_transform(inv_yhat)
inv_yhat = inv_yhat[:,-1]
# invert scaling for actual
test_y = test_y.reshape((len(test_y), 1))
```

```
inv_y = concatenate((test_X[:, -22:], test_y), axis=1)
inv_y = scaler.inverse_transform(inv_y)
inv_y = inv_y[:,-1]
# calculate RMSE

print("----***----***----")
print(inv_y)
print(inv_yhat)
rmse = sqrt(mean_squared_error(inv_y, inv_yhat))
print('Test RMSE: %.3f' % rmse)

export = DataFrame([inv_y, inv_yhat]).T
export.to_csv("test_final.csv", index=False)
```

Listing A.4: LSTM Network

References

[1] M. Alaqtash, T. Sarkodie-Gyan, H. Yu, O. Fuentes, R. Brower, and A. Abdelgawad. "Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms". In: *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*. IEEE. 2011, pp. 453–457 (cit. on p. 3).

[2] J. Barton and A. Lees. "An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams". In: *Gait & posture* 5.1 (1997), pp. 28–33 (cit. on p. 22).

[3] R. K. Begg, M. Palaniswami, and B. Owen. "Support vector machines for automated gait classification". In: *IEEE transactions on Biomedical Engineering* 52.5 (2005), pp. 828–838 (cit. on p. 19).

[4] A.-K. Berger, L. Fratiglioni, Y. Forsell, B. Winblad, and L. Bfffdfffdckman. "The occurrence of depressive symptoms in the preclinical phase of AD A population-based study". In: *Neurology* 53.9 (Dec. 1, 1999), pp. 1998–1998. ISSN: 0028-3878, 1526-632X. DOI: 10.1212/WNL.53.9.1998. URL: http://www.neurology.org/content/53/9/1998 (visited on 08/29/2017) (cit. on p. 7).

[5] J. Brownlee. *How to Use Timesteps in LSTM Networks for Time Series Forecasting*. Aug. 2018. URL: https://machinelearningmastery.com/use-timesteps-lstm-networks-time-series-forecasting/ (cit. on p. 69).

[6] T. Buracchio, H. H. Dodge, D. Howieson, D. Wasserman, and J. Kaye. "The trajectory of gait speed preceding mild cognitive impairment". In: *Archives of neurology* 67.8 (2010), pp. 980–986 (cit. on p. 28).

[7] T. Chau. "A review of analytical techniques for gait data. Part 2: neural network and wavelet methods". In: *Gait & posture* 13.2 (2001), pp. 102–120 (cit. on pp. 20, 22, 23).

[8] P. Chowriappa, S. Dua, and Y. Todorov. "Introduction to machine learning in healthcare informatics". In: *Machine Learning in Healthcare Informatics*. Springer, 2014, pp. 1–23 (cit. on p. 5).

[9] G. Eysenbach. "Recent advances: Consumer health informatics". In: *BMJ: British Medical Journal* 320.7251 (2000), p. 1713 (cit. on p. 5).

[10] M. Gadaleta and M. Rossi. "Idnet: Smartphone-based gait recognition with convolutional neural networks". In: *Pattern Recognition* 74 (2018), pp. 25–37 (cit. on pp. 15, 22).

[11] Y. Gal and Z. Ghahramani. "A theoretically grounded application of dropout in recurrent neural networks". In: *Advances in neural information processing systems*. 2016, pp. 1019–1027 (cit. on p. 37).

[12] S. Gauthier, B. Reisberg, M. Zaudig, R. C. Petersen, K. Ritchie, K. Broich, S. Belleville, H. Brodaty, D. Bennett, H. Chertkow, J. L. Cummings, M. de Leon, H. Feldman, M. Ganguli, H. Hampel, P. Scheltens, M. C. Tierney, P. Whitehouse, and B. Winblad. "Mild cognitive impairment". In: *The Lancet*

367.9518 (Apr. 15, 2006), pp. 1262–1270. ISSN: 0140-6736. DOI: 10.1016/S0140-6736(06)68542-5. URL: http://www.sciencedirect.com/science/article/pii/S0140673606685425 (visited on 08/22/2017) (cit. on p. 7).

[13] G. Gioftsos and D. Grieve. "The use of neural networks to recognize patterns of human movement: gait patterns". In: *Clinical Biomechanics* 10.4 (1995), pp. 179–183 (cit. on p. 22).

[14] K. R. Gray, P. Aljabar, R. A. Heckemann, A. Hammers, D. Rueckert, A. D. N. Initiative, et al. "Random forest-based similarity measures for multi-modal classification of Alzheimer's disease". In: *NeuroImage* 65 (2013), pp. 167–175 (cit. on p. 18).

[15] J. Hannink, T. Kautz, C. F. Pasluosta, K.-G. Gaßmann, J. Klucken, and B. M. Eskofier. "Sensor-based gait parameter extraction with deep convolutional neural networks". In: *IEEE journal of biomedical and health informatics* 21.1 (2017), pp. 85–93 (cit. on p. 22).

[16] J. M. Hausdorff and A. S. Buchman. *What links gait speed and MCI with dementia? A fresh look at the association between motor and cognitive function.* 2013 (cit. on pp. 9, 11).

[17] B. W. Heller, P. H. Veltink, N. J. Rijkhoff, W. L. Rutten, and B. J. Andrews. "Reconstructing muscle activation during normal walking: a comparison of symbolic and connectionist machine learning techniques". In: *Biological cybernetics* 69.4 (1993), pp. 327–335 (cit. on p. 22).

[18] M. Heydarzadeh, C.-T. Tan, M. Nourani, and S. Ostadabbas. "Gait variability assessment in neuro-degenerative patients by measuring complexity of independent sources". In: *Engineering in Medicine and Biology Society (EMBC), 2017*

39th Annual International Conference of the IEEE. IEEE. 2017, pp. 3186–3189 (cit. on pp. 10, 11).

[19] T. K. Ho. "Random decision forests". In: *Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on*. Vol. 1. IEEE. 1995, pp. 278–282 (cit. on p. 18).

[20] S. Hochreiter. "The vanishing gradient problem during learning recurrent neural nets and problem solutions". In: *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 6.02 (1998), pp. 107–116 (cit. on p. 23).

[21] S. Hochreiter and J. Schmidhuber. "Long short-term memory". In: *Neural computation* 9.8 (1997), pp. 1735–1780 (cit. on p. 23).

[22] S. Hochreiter, Y. Bengio, P. Frasconi, J. Schmidhuber, et al. *Gradient flow in recurrent nets: the difficulty of learning long-term dependencies*. 2001 (cit. on p. 23).

[23] S. H. Holzreiter and M. E. Köhle. "Assessment of gait patterns using neural networks". In: *Journal of biomechanics* 26.6 (1993), pp. 645–651 (cit. on p. 21).

[24] T. IJmker and C. J. Lamoth. "Gait and cognition: the relationship between gait stability and variability with executive function in persons with and without dementia". In: *Gait & posture* 35.1 (2012), pp. 126–130 (cit. on pp. 13, 15).

[25] J. Juen, Q. Cheng, V. Prieto-Centurion, J. A. Krishnan, and B. Schatz. "Health monitors for chronic disease by gait analysis with mobile phones". In: *Telemedicine and e-Health* 20.11 (2014), pp. 1035–1041 (cit. on p. 15).

[26] B. L. Kalman and S. C. Kwasny. "Why tanh: choosing a sigmoidal function". In: *[Proceedings 1992] IJCNN International Joint Conference on Neural Networks*. Vol. 4. IEEE. 1992, pp. 578–581 (cit. on p. 39).

[27] D. P. Kingma and J. Ba. "Adam: A method for stochastic optimization". In: *arXiv preprint arXiv:1412.6980* (2014) (cit. on p. 39).

[28] C. Kirkwood, B. Andrews, and P. Mowforth. "Automatic detection of gait events: a case study using inductive learning techniques". In: *Journal of biomedical engineering* 11.6 (1989), pp. 511–516 (cit. on p. 3).

[29] D. S. Knopman. "The initial recognition and diagnosis of dementia". In: *The American journal of medicine* 104.4 (1998), 2S–12S (cit. on pp. 8, 9, 11).

[30] K. Kong and M. Tomizuka. "A Gait Monitoring System Based on Air Pressure Sensors Embedded in a Shoe". In: *IEEE/ASME Transactions on Mechatronics* 14.3 (June 2009), pp. 358–370. ISSN: 1083-4435. DOI: 10.1109/TMECH.2008.2008803 (cit. on p. 14).

[31] I. Kononenko. "Machine learning for medical diagnosis: history, state of the art and perspective". In: *Artificial Intelligence in medicine* 23.1 (2001), pp. 89–109 (cit. on pp. 17, 24).

[32] D. T. H. Lai, M. Palaniswami, and R. Begg. *Healthcare sensor networks: challenges toward practical implementation*. CRC Press, 2011 (cit. on pp. 12, 16).

[33] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell. "A survey of mobile phone sensing". In: *IEEE Communications magazine* 48.9 (2010) (cit. on p. 14).

[34] D. Lee and J. Lishman. "Visual proprioceptive control of stance." In: *Journal of human movement studies* (1975) (cit. on p. 9).

[35] B. P. Leifer. "Early Diagnosis of Alzheimer's Disease: Clinical and Economic Benefits". In: *Journal of the American Geriatrics Society* 51.5 (May 1, 2003), S281–S288. ISSN: 1532-5415. DOI: 10.1046/j.1532-5415.5153.x. URL: http:

//onlinelibrary.wiley.com/doi/10.1046/j.1532-5415.5153.x/abstract (visited on 08/22/2017) (cit. on p. 4).

[36] L. Lemos. "A data mining approach to predict conversion from mild cognitive impairment to Alzheimerfffdfffdfffds Disease". PhD thesis. Masterfffdfffdfffds thesis, IST, 2012 (cit. on p. 16).

[37] S. Liao and B. A. Ferrell. "Fatigue in an older population". In: *Journal of the American Geriatrics Society* 48.4 (2000), pp. 426–430 (cit. on p. 27).

[38] E. O. Lillie, B. Patay, J. Diamant, B. Issell, E. J. Topol, and N. J. Schork. "The n-of-1 clinical trial: the ultimate strategy for individualizing medicine?" In: *Personalized medicine* 8.2 (2011), pp. 161–173 (cit. on p. 5).

[39] O. L. Mangasarian, W. N. Street, and W. H. Wolberg. "Breast cancer diagnosis and prognosis via linear programming". In: *Operations Research* 43.4 (1995), pp. 570–577 (cit. on p. 17).

[40] N. Mijailovic, M. Gavrilovic, S. Rafajlovic, M. uric-Jovicic, and D. Popovic. "Gait phases recognition from accelerations and ground reaction forces: Application of neural networks". In: *Telfor Journal* 1.1 (2009), pp. 34–36 (cit. on p. 22).

[41] A. Miller. "Gait event detection using a multilayer neural network". In: *Gait & posture* 29.4 (2009), pp. 542–545 (cit. on p. 22).

[42] S. C. Mukhopadhyay. "Wearable Sensors for Human Activity Monitoring: A Review". In: *IEEE Sensors Journal* 15.3 (Mar. 2015), pp. 1321–1330. ISSN: 1530-437X. DOI: 10.1109/JSEN.2014.2370945 (cit. on p. 12).

[43] A. Muro-De-La-Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla. "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications". In: *Sensors* 14.2 (2014), pp. 3362–3394 (cit. on pp. 13, 14).

[44] D. L. Nyenhuis and P. B. Gorelick. "Vascular Dementia: A Contemporary Review of Epidemiology, Diagnosis, Prevention, and Treatment". In: *Journal of the American Geriatrics Society* 46.11 (Nov. 1, 1998), pp. 1437–1448. ISSN: 1532-5415. DOI: 10.1111/j.1532-5415.1998.tb06015.x. URL: http://onlinelibrary.wiley.com/doi/10.1111/j.1532-5415.1998.tb06015.x/abstract (visited on 08/22/2017) (cit. on p. 4).

[45] M. Panahiazar, V. Taslimitehrani, A. Jadhav, and J. Pathak. "Empowering personalized medicine with big data and semantic web technology: promises, challenges, and use cases". In: *Big Data (Big Data), 2014 IEEE International Conference on*. IEEE. 2014, pp. 790–795 (cit. on p. 6).

[46] M. J. Pazzani, S. Mani, W. R. Shankle, et al. "Acceptance of rules generated by machine learning among medical experts". In: *Methods of information in medicine* 40.5 (2001), pp. 380–385 (cit. on p. 24).

[47] K. Rockwood, C. Macknight, C. Wentzel, S. Black, R. Bouchard, S. Gauthier, H. Feldman, D. Hogan, A. Kertesz, and P. Montgomery. "The diagnosis of fffdfffdfffdmixedfffdfffdfffd dementia in the Consortium for the Investigation of Vascular Impairment of Cognition (CIVIC)". In: *Annals of the New York Academy of Sciences* 903.1 (2000), pp. 522–528 (cit. on p. 8).

[48] G. C. Román and D. R. Royall. "Executive control function: a rational basis for the diagnosis of vascular dementia." In: *Alzheimer disease and associated disorders* (1999) (cit. on p. 1).

[49] G. C. Romfffdfffdn et al. “Vascular dementia Diagnostic criteria for research studies: Report of the NINDSfffdfffdfffdAIREN International Workshop*”. In: *Neurology* 43.2 (Feb. 1, 1993), pp. 250–250. ISSN: 0028-3878, 1526-632X. DOI: 10.1212/WNL.43.2.250. URL: http://www.neurology.org/content/43/2/250 (visited on 08/22/2017) (cit. on p. 57).

[50] D. L. Sackett. “Evidence-based medicine”. In: *Seminars in perinatology*. Vol. 21. 1. Elsevier. 1997, pp. 3–5 (cit. on p. 5).

[51] E. Scherder, L. Eggermont, D. Swaab, M. van Heuvelen, Y. Kamsma, M. de Greef, R. van Wijck, and T. Mulder. “Gait in ageing and associated dementias; its relationship with cognition”. In: *Neuroscience & Biobehavioral Reviews* 31.4 (2007), pp. 485–497 (cit. on p. 1).

[52] F. Sepulveda, D. M. Wells, and C. L. Vaughan. “A neural network representation of electromyography and joint dynamics in human gait”. In: *Journal of biomechanics* 26.2 (1993), pp. 101–109 (cit. on p. 22).

[53] R. A. Sperling et al. “Toward defining the preclinical stages of Alzheimerfffdfffdfffds disease: Recommendations from the National Institute on Aging-Alzheimer’s Association workgroups on diagnostic guidelines for Alzheimer’s disease”. In: *Alzheimer’s & Dementia* 7.3 (May 1, 2011), pp. 280–292. ISSN: 1552-5260. DOI: 10.1016/j.jalz.2011.03.003. URL: http://www.sciencedirect.com/science/article/pii/S1552526011000999 (visited on 08/29/2017) (cit. on p. 7).

[54] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. “Dropout: a simple way to prevent neural networks from overfitting”. In: *The Journal of Machine Learning Research* 15.1 (2014), pp. 1929–1958 (cit. on p. 37).

[55] B. C. Stephan, F. E. Matthews, K.-T. Khaw, C. Dufouil, and C. Brayne. "Beyond mild cognitive impairment: vascular cognitive impairment, no dementia (VCIND)". In: *Alzheimer's Research & Therapy* 1.1 (July 9, 2009), p. 4. ISSN: 1758-9193. DOI: 10.1186/alzrt4. URL: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2719105/ (visited on 08/22/2017) (cit. on p. 7).

[56] J. A. Suykens and J. Vandewalle. "Least squares support vector machine classifiers". In: *Neural processing letters* 9.3 (1999), pp. 293–300 (cit. on p. 19).

[57] G. G. Szpiro. "Forecasting chaotic time series with genetic algorithms". In: *Physical Review E* 55.3 (1997), p. 2557 (cit. on p. 25).

[58] J. Verghese, R. B. Lipton, C. B. Hall, G. Kuslansky, M. J. Katz, and H. Buschke. "Abnormality of Gait as a Predictor of Non-Alzheimer's Dementia". In: *New England Journal of Medicine* 347.22 (Nov. 28, 2002), pp. 1761–1768. ISSN: 0028-4793. DOI: 10.1056/NEJMoa020441. URL: http://dx.doi.org/10.1056/NEJMoa020441 (visited on 09/22/2017) (cit. on p. 57).

[59] J. Verghese, R. B. Lipton, C. B. Hall, G. Kuslansky, M. J. Katz, and H. Buschke. "Abnormality of gait as a predictor of non-Alzheimer's dementia". In: *New England Journal of Medicine* 347.22 (2002), pp. 1761–1768 (cit. on pp. 1, 10).

[60] J. Verghese, C. Wang, R. B. Lipton, R. Holtzer, and X. Xue. "Quantitative gait dysfunction and risk of cognitive decline and dementia". In: *Journal of Neurology, Neurosurgery & Psychiatry* 78.9 (2007), pp. 929–935 (cit. on pp. 1, 9–11, 25, 26, 35).

[61] V. J. A. Verlinden, J. N. van der Geest, R. F. A. G. de Bruijn, A. Hofman, P. J. Koudstaal, and M. A. Ikram. "Trajectories of decline in cognition and daily functioning in preclinical dementia". In: *Alzheimer's & Dementia* 12.2 (Feb. 1, 2016), pp. 144–153. ISSN: 1552-5260. DOI: 10.1016/j.jalz.2015.

08.001. URL: http://www.sciencedirect.com/science/article/pii/S1552526015027004 (visited on 08/29/2017) (cit. on p. 7).

[62] L. Waite, D. Grayson, O. Piguet, H. Creasey, H. Bennett, and G. Broe. "Gait slowing as a predictor of incident dementia: 6-year longitudinal data from the Sydney Older Persons Study". In: *Journal of the neurological sciences* 229 (2005), pp. 89–93 (cit. on p. 1).

[63] J.-H. Yoo, D. Hwang, K.-Y. Moon, and M. S. Nixon. "Automated human recognition by gait using neural network". In: *2008 First Workshops on Image Processing Theory, Tools and Applications*. IEEE. 2008, pp. 1–6 (cit. on p. 20).